SIMULATION MODELLING IN MARINE FISHERIES FOR FISH STOCK ASSESSMENT A BIO-STATISTICAL ANALYSIS

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DEDICATED TO MEMORY OF MY BELOVED PARENTS

CERTIFICATE

This is to certify that this Thesis entitled **Simulation Modelling in Marine Fisheries for Fish Stock Assessment - A Bio- Statistical Analysis** submitted to the University of Calicut for the award of **Degree of Doctor of Philosophy in Statistics** is a record of original research work done by M. Srinath during the period of his study in the Department of Statistics, University of Calicut, Kerala, under my supervision and guidance and the Thesis has not formed the basis for award of any Degree/Diploma/Associateship/Fellowship or similar title to any candidate of any University or Institute.

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DECLARATION

I hereby declare that the matter embodied in this Thesis is the result of investigations carried out by me in the Department of Statistics, University Of Calicut, under the supervision and guidance of Dr. K. Kumaran Kutty, Head & Professor, Department of Statistics, University of Calicut and it has not been submitted for award of any Degree/Diploma/Asssociateship/Fellowship of any other University or Institute.

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INTRODUCTION

INTRODUCTION

Marine fisheries in India has emerged as a significant contributor to the economy of the country. From a meagre annual catch of about 5 lakh tonnes in the early fifties, it has shot upto about 22 lakh tonnes during the nineties. Such a phenomenal growth was as the result of realisation of export potential of marine products especially the shrimps, and subsequent increase in the demand for other marine products both globally and internally. This triggered the development of innovative methods of fishing practices through improvements in the craft and gear and also by way of extending the fishing grounds. Traditional fishing scenario, operating within a narrow depth range of about 30 m, has transformed into a complex mechanised sector leading to a multigear and multispecies system. Increased fishing pressure from a particular sector brought in its wake the associated problems of intersectoral conflicts, resource threats and signs of eco-degradation. Thus, to understand such a dynamic and complex system, constant and continuous monitoring is essential. Besides, it has become imperative to carryout stock assessment on a regular basis, for judicious exploitation of the stocks.

John Gulland (1974) has categorised the main questions faced by fishery managers as follows:

(a) How big is the resource and how many fish can be caught each year while maintaining the stock for the future ?

(b) Given the potential catch how should this be used for the greatest benefit of the country ?

(c) What actions need to be taken to achieve these objectives ?

This obviously requires an exercise in resource (stock) evaluation or assessment. Fish stock assessment is a technique of providing advice on fisheries management. It is done through assessment of long-term and short-term potential of the biological resources as a whole as well as of its various components and their inter-relationships.

In fish stock assessment there are two types of models that are employed to study the dynamics of the fish populations. One is the micro or analytical models (or methods) and the other the macro or global (surplus production) models. Models that can be solved in closed form mathematically are analytical models. For such models a general solution can be obtained which is applicable to all situations the model can represent. In analytical models we take into consideration the various components that affect the stock, namely, growth, mortality, size or age at capture etc. In macro models we deal with only the observable inputs (say fishing effort) and the actual outputs (yield in weight) from a given population. The main features which attract the fishery biologist to use these models are (i) they are simple models (ii) the data requirements are limited and (iii) computational ease in estimating the model parameters.

To describe the effects of fisheries on fish stocks, it is necessary not only to know a great deal about the stocks but also to have an intimate knowledge of the fisheries themselves. It is necessary to know the quantities of each species removed, the time and location of removal and the size and age composition of the catch. For a proper evaluation of the stock, statistics of catch and effort along with those of relevant biological characteristics are essential over time and space. Needless to say, the validity of the resource evaluation depends largely on the precision of the data base which is governed by the scheme of data collection which includes mode and frequency of collection. In India, marine fish catch statistics are collected from 1950's following the principles of statistical sampling theory. This study examines the aspects of the precision of the estimates of catch statistics and also the frequency of data collection on a case study basis.

Having collected the required data for resource evaluation, the next step would obviously be to search or explore an appropriate model/method that would amply describe the underlying process and estimate the parameters that govern the process. This requires application of mathematics and statistics .

The use of mathematical models in fisheries work was established in the late 1950's by Beverton and Holt. Building on this corner stone many fishery scientists, statisticians and mathematicians gradually developed various mathematical models which have greatly helped in understanding the system. We will focus primarily on the use of some of the most commonly used models in fisheries within a management oriented framework and their role in providing information for the decision making process. Obviously, such usage involves developing quantitative models predicting effects of management options(or policies) on the fisheries systems. Application of mathematical models to assess fish stocks is the core of resource evaluation activity.

Model formulation is an important exercise in fish stock assessment. The purpose is not only to evaluate the magnitude and variations in the various parameters of the fishery but also formulate guidelines for harvesting strategies for rational exploitation of the stocks on a short term and long term basis. This calls for checking the validity of the chosen model from time to time. Similarly, there can be different manifestations of a model (which can be termed as "derived forms") and one can choose an appropriate derived form depending upon the requirements and needs. Thus, the exercise in model evaluation is an important aspect of resource assessment in judging its performance in respect of its ability to estimate the components of the underlying process more precisely and provide meaningful predictions, if necessary. If the system is simple enough, it may be possible to derive analytical solutions to the parameter estimation. It is well known that exploited fish populations are not only governed by fishery dependent factors but also by fishery independent factors. Traditionally, the approach to modelling in fisheries focused on the inter-relationship of fishery dependent factors and the yield. The other factors are clubbed with "random noises" or assumed in the long run to cancel out each other. A simple approach is to ignore uncertainty and random fluctuations. Such an approach leads to static, deterministic models. Application of such models for highly dynamic fish populations living in a fluctuating environment may lead to hazardous results. Thus, it is imperative to consider the various sources of bias, and variation in estimating the parameters of the model for a proper understanding of the system and how the model parameters and the functions of the parameters react to "noise" caused by the various sources of bias and variations. This aspect is also dealt with in the present study.

Analytical models are developed as functions of individual components of the system such as the recruitment, growth, mortality, etc. There are various approaches in estimating these parameters either singly or in combination (Sparre and Venema 1992). These parameters are vital to stock assessment, the harvesting strategies depend upon the reliability of the estimates of the parameters. Comparative efficiencies in terms of bias and variation of some of the commonly used estimates of parameters are explored in the present study. An alternative algorithm for length cohort analysis also is presented.

The goal of model formulation in fisheries is not only to describe the input-output relationship to develop suitable exploitation options but also to make predictions in the short term and long term basis. The classical models in fisheries mainly deal with the long term aspects. There are some empirical models which deal with the short term objectives of the resource users, Auto Regressive Integrated Moving Average(ARIMA) modelling, is one such approach dealt with in this study which has been applied to marine fisheries of India.

Most populations of plants and animals tend to increase after dipping to unusually low densities (at which point, the conditions become most suitable for growth) and after reaching unusually high densities, they tend to decrease again (May, 1992). One of the main aim of the population studies is to discover the factors that regulate the population. Such understanding is not only fundamentally important, but it also has practical applications in trying to predict the likely effects of natural or man-made changes such as those that occur where a population is harvested or a climate pattern is altered. These disturbances in the long run, produce periodic or cyclic variations in the populations. According to Kaitala *et al.* (1996), different biological and ecological dynamics are capable of producing periodic type of response to environmental perturbations. This aspect is examined in this study in the case of the oil sardine one of the most important pelagic fin fish resource of India.

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CHAPTER I

CHAPTER I

BOOT STRAP EVALUATION OF THE SAMPLING SCHEME TO ESTIMATE THE MARINE FISH LANDINGS

I.1 Introduction

Exploited fish stocks are assessed with the help of micro analytic and macro models (Alagaraja, 1990). Catch in numbers (age specific or length specific) or catch in weight and the corresponding fishing effort expended are the main inputs to the fish population models. The quality of this input data governs the performance (predictive or interpolative) of the models and determines the relevance of management decisions inferred from the stock assessment studies.

Catches usually are estimated from sampling of commercial landings. These sampling schemes are often complex and multistage in nature. In India marine fish catch statistics are collected by the Central Marine Fisheries Research Institute, Cochin through a sampling system based on the theory of sampling(Banerji, 1971). Most of the catches are from the inshore regions and landed at about 2400 landing centres spread all along the coast line in the various maritime states of India. Keeping pace with the changing pattern of the fishery the mode of collection has also undergone change periodically without any significant alterations in the basic structure of the sampling design.

The sampling design followed by the Central Marine Fisheries Research Institute during 1970s and before was explained by Kutty *et.al.*(1973). With the spurt in the implementation of mechanization in the fishing industry the quantity and quality of data to be collected increased tremendously. Taking this into account the concept of Single Centre Zone was introduced meaning a particular centre at which there was intense mechanized activity. The mode of collection during the late 1970s and early part of 1980s was described by Jacob *et.al.*(1983). Later, the mode of collection underwent slight change with respect to selection of crafts and the modified sampling scheme was given by Alagaraja (*op.cit.*). For the sake of completeness the sampling procedure currently followed is described hereunder.

In the sampling scheme of the CMFRI the stratification is done over space and time. The stratification over space is made by dividing each maritime state into suitable , compact and non-overlapping zones on the basis of fishing intensity and geographical consideration. The stratum over time is a calendar month . The month is divided into 3 ten-day groups. From the first group, from among the first five days , a day is selected at random and starting from this day 3 clusters of two days each are made. From the second and the third ten-day groups the clusters are selected with a sampling interval of 10 days. From a zone , 9 centres are selected with replacement and allotted to the above 9 clusters of 2 days each. For a selected centre, on the allotted first day observations are made from 1200 to 1800 hours and on the second day of the allotted cluster the observations are made from 0600 to 1200 hours. The details on the landings after 1800 hours on the first day and upto 0600 hours on the second day are obtained by enquiry. Thus we have information for a 24 hour period for the selected landing centre. This is termed as the landing centre - day and thus forms the first stage unit of the sampling.

During the period of observation at the selected centre on the specified day, the boats landing with the catch are selected at random systematically with a predetermined sampling interval depending on the number of boats landing their catches. From the selected boat , the information on the species-wise catch , the effort expended and other relevant details are obtained. From this , the total catch for that day is estimated and monthly estimates are obtained by adding the estimated total catches on the observed days and multiplying by an appropriate raising factor. Thus, for estimating the marine fish landings the design basically is a two-stage scheme with the landing centre-days forming the primary stage units and the boats landing their catches on the day of observation forming the second stage units. Keeping in view the magnitude and intensity of fishing operations and infrastructure facilities, certain landing centres are treated zones as themselves and are termed as single centre zones. At these zones the basic sampling scheme is same as that at the other zones.

The estimation of the catch is straightforward and does not need any elaboration. It is known that if the first stage units are selected with replacement and the second stage units are selected systematically then the estimate of the variance reduces only due to that among the first stage units (Sukhatme and Sukhatme, 1970). However, in this case the first stage units are the landing centre days which are not selected with replacement but only the landing centres. Thus, in this case estimation of variance poses a problem. Another important aspect is the sample size. It is important to know the optimum sample size for a desired level of precision. Are the currently observed number of days and the boats selected on the selected day adequate enough for estimating the total catch for a specified level of precision? This question can be answered if an estimate of the variance is available with us (Here the total cost of the survey is not considered). In this study an attempt is made to answer the above question.

Covering all the zones in the country (or even all the zones in a state) is beyond the means of the resources available with the Investigator. So for this study only a Single Centre Zone is considered as a case study. Cochin Fisheries Harbour one of the most important landing centres in Kerala where large number of mechanized boats operate is hence selected for the study. The data were collected during January 1992 to December 1993 as per the sampling plan described earlier . At this centre, catches from trawlers, drift-gillnetters, hooks & lines, ring-seine and purse-seine are landed, of these, the catches by trawlers form the major component of the total landings and thus only trawl catches were estimated.

The Monte Carlo Bootstrap methodology was applied to evaluate the sampling scheme in terms of estimates of the coefficient of variation and determining the sample number of days for observation. *Kimura and Balsiger (1985) pointed out that one could spend considerable time and effort fitting these data into* *classical sampling theory. Alternatively, the bootstrap method uses the well-defined structure of the survey to define an empirical process. This sample is processed repeatedly using Montecarlo methods and the resulting variability analyzed.* According to Efron (1982) the important theme of resampling methods such as Bootstrap is the substitution of computational power for theoretical analysis. The bootstrap can routinely answer questions which are too complicated for traditional statistical analysis.

I. 2 REVIEW

I.2.1 Evaluation of CMFRI sampling scheme

Except for a study by Kutty *et.al* (*op.cit.*) there had been no attempt to evaluate the sampling design of CMFRI in terms of the precision of the estimates and deriving optimum sample size. They tried to answer (1) to what extent the catch statistics at the all India level and at the state level were accurate (2) whether any improvement in the sampling procedure was possible and (3) whether the sampling fraction which depended on the number of survey staff should be increased. They arrived at certain conclusions based on the then existing sampling scheme and some simplistic assumptions on the primary stage units. They concluded that the sampling design followed by CMFRI was scientifically sound; the procedure gave fairly reliable estimates of the total all India fish landings; the statewise estimates though less accurate were nevertheless realistic; and suggested redistribution of field staff on the basis of optimum allocation. Their study concentrated mainly on the sampling coverage on all India basis and allocation of field staff to the east and west coast of India based on the survey results from 1966 to 1970.

Alagaraja and Srinath (1980) attempted to estimate the reliability of the estimates of marine fish landings in India by regressing the estimated landings with the quantity exported during the corresponding year. They concluded that the precision of the estimates obtained through sample survey of the CMFRI were within the acceptable range.

I.2.2 Bootstrap methodology

The bootstrap is a computer based resampling methodology aimed at estimating the standard error of a complex sample statistic and establish its confidence intervals. Efron(1979) advocated the use of Simple Random Sampling with replacement for resampling data and gave it a catchy name ***Bootstrap***. Efron and Tibshirani (1986) gave description of the bootstrap sampling. The bootstrap algorithm as explained by Efron (1991) is as follows.

Let $(x_1,x_2,......x_n)$ be independently and identically distributed observations from a unknown probability distribution F. From $(x_1,x_2,......x_n)$ we calculate a statistic of interest $S(x_1,x_2,......x_n)$ the numerical value of which we call S^o. Let F indicate the empirical probability distribution function putting probabilities 1/n on each observed value x_i (i=1,2,....n). A bootstrap sample $(X_1^*,X_2^*,.....X_n^*) = X^*$ is a random sample of size n from F. Each X_i^* independently equals x_i with probability 1/n(i=1,2...n). The statistic of interest S evaluated for the bootstrap data X^* is a bootstrap replication S^*. Now, we have only one value of original statistic S^o but we can generate by Monte Carlo sampling as many bootstrap replications S^*. Let $X^*_1,X^*_2.....X^*_B$ be independent bootstrap samples. Each X^{*b} gives an independent bootstrap replication of the statistic of interest say $S(X^{*b}) = S^b$ (b=1,2....B). The bootstrap replications provide bias and variance estimates in a straight forward way as described in Efron and Tibshirani(*op.cit.*)

$$\text{bias} = \bar{S} - S^o \quad \text{and} \quad \bar{S} = \sum S^b / B$$

$$\text{varB} = \sum (S^b - \bar{S})^2 /(B-1)$$

These can be made use to estimate the coefficient of variation and construct the confidence intervals.

More sophisticated methods of drawing the Monte Carlo samples than the simple random sampling from F are given by Davison *et. al* (1986) and Graham *et.al* (1987). For the purpose of this study only the simple bootstrap (*naive* bootstrap) is considered because of its ease in computation.

I.2.3 Bootstrap application in theory of sample survey

Bickel and Freedman (1984) applied bootstrap technique in stratified sampling. Chao and Lo (1985) proposed a different bootstrap sampling method for finite populations.

Rao and Wu (1988) investigated the extension of i.i.d. bootstrap to complex survey data especially those obtained from stratified cluster sampling. They proposed 'a correct' bootstrap method for stratified samples and studied properties of the resulting variance estimators. They also proposed several sampling methods for unequal probability sampling without replacement. They also extended the bootstrap method to two-stage cluster sampling with equal probabilities and without replacement. Results of a simulation study under a stratified simple random sampling design showed that bootstrap intervals track nominal error rate in each trial better than the intervals based on normal approximation but the bootstrap variance estimators were less stable than those based on linearization or the jackknife.

Sitter(1991) also explored the extensions of the bootstrap to complex survey data where sampling was without replacement. A resampling method without replacement was proposed. The properties of the resulting variance estimators and an estimate of bias were explored. The simulation analysis carried out by him also revealed more or less identical results as obtained by Rao and Wu (*op.cit.*).

I.2.4 Bootstrap application to fishery surveys

Studies on bootstrap evaluation of complex surveys in fisheries have not been many and there has not been any such attempt in India. Kimura and Balsiger (*op.cit.*) applied the bootstrap methods to evaluate sable fish pot index surveys in the north east Pacific Ocean. The goal of the pot index surveys was to provide estimates of average annual catch per set which could be followed through the time to provide indices of inter-annual relative abundance. The purpose of the study was to evaluate the sablefish pot index survey base statistically and make recommendations concerning future design and sample sizes. Analysis of variance (ANOVA) and the Monte Carlo bootstrap (Efron 1982) were used to evaluate the survey data base. ANOVA was used to examine the statistical significance of survey design variables. The Monte Carlo bootstrap was used to evaluate the effect of varying the number of locations sampled and the number of sets made with in each depth stratum at a location. This was done in two ways. First bootstrap estimates of the coefficient of variation of the annual average catch per set were calculated. These estimates gave some indicators of how well mean annual abundance would be measured at various sampling levels.

Second, the bootstrap was used to estimate a Z-statistic (between years) which indicated the statistical significance of observed mean differences at various sampling levels.

The bootstrap process proceeded by first arranging a given year's data so that they were indexed by location ,depth and set within location and depth, then the following steps were taken.

1. A location was randomly selected

2. Depths then were systematically sampled. At each depth within the selected location, the required number of sets were randomly selected and the observed catch per set recorded.

3. Steps (1) and (2) were repeated until the required number of locations were sampled. Using the bootstrap, sampling was always with replacement.

Let X_{ijkl} be the bootstrap observation (catch per set) for year i, location j, depth k and set l. For a given sampling level (say J location K=4 depths and L sets) an abundance index can be calculated as

$$\bar{X}i^{(b)} = \sum_{j}^{J}\sum_{k}^{4}\sum_{l}^{L} X_{ijkl} / J4L$$

where 'b' indicates the b^{th} bootstrap abundance index. Repeating the entire process B times (say B=1000) a bootstrap estimate of the mean and the variance of the X_i can be calculated from the mean and variance of the individual X_ib 's. The bootstrap is unbiased in this case and the mean is calculated as the sample mean of the actual data. This mean can be used to check the simulation results and also to calculate the variance estimate

$$V(\bar{X}_i) = \sum (\bar{X}_i{}^{b} - \mu_i)^2 / B$$

$$\text{s.d.} = \sqrt{(V(\bar{X}_i))}$$

Estimate of coefficient of variation (C.V.)$\bar{X}i$ =(s.d. $/\mu_i$) x 100

Bootstrap estimates of C.V of $\bar{X}_i$, the average catch per set in pounds were calculated for sampling levels J = 3,6,9,12 and 15 locations and L = 1,3,5,7 and 9 sets. The results indicated that the increasing the number of locations could effectively reduce the estimated C.V whereas increasing the number of sets had remarkably little effect. From these they concluded that more locations should be sampled with fewer sets made at each location. They had also made comparison of bootstrap estimate of CV with the estimate for two stage sampling theory. This revealed excellent comparison of bootstrap estimates with the estimates derived from the two stage sampling. They further observed that when the between location variability was large there was little benefit from increasing the number of sets sampled within a location.

Pelletier and Gros (1991) studied the propagation of sampling errors in catches to a yield model using virtual population analysis for which catch at age data was essential. The errors were assessed from three techniques, the delta method, Gaussian approximation and the bootstrap. The age specific catches were estimated from sampling of commercial landings and a detailed description of the sampling procedure was given. The three approaches were then compared in terms of required initial assumptions , types of results and probable accuracy of variance estimator. Their analysis indicated that bootstrap provided lower coefficient of variation values than the delta method. The bootstrap was more informative than the analytical approach and it provided the distribution of yield per recruit replicates in addition to mean values and variance estimates. They also found that the variance estimates from bootstrap and Gaussian approximation were quite close. In respect of reliability of variance estimators they contended that the bootstrap results were likely to be closer to reality.

Stanely (1992) used the bootstrap analysis to examine the variance in trawl catch per unit effort(CPUE) for four fisheries along the Canada's Pacific coast. The resulting confidence limits based on the bias corrected percentile method indicated that the variance in CPUE varied widely among the fisheries. Depending on the fishery 20 to 100 randomly selected observations per year were required to provide minimally sufficient precision for stock assessment.

Thus the review revealed usefulness of the bootstrap methodology in complex surveys as the sample surveys for collection of marine fish catch statistics. Since in the Indian context no study was carried to assess the fishery sampling scheme, the present work could be considered a precursor to the ensuing studies in evaluating the fishery surveys. Bootstrap technique was applied in the present case making certain assumptions on the sampling scheme which from the practical point of view seem quite tenable.

I.3 Methodology and Data base

I.3.1 Sampling scheme for collection of data

A month was divided into 3 ten day groups. From the first ten day group from among the first five days, a day was selected at random. Starting from this day, 3 clusters of two days each were formed. From the remaining two ten day groups , the clusters were selected with interval of 10 days. For example, from the first five days if the day selected was 3, then the three clusters in the first ten day group were (3,4),(5,6) and (7,8). Then from the next two ten day-groups,clusters would be (13,14),(15,16),(17,18),(23,24),(25,26) and (27,28). Thus we have 9 clusters of 2 days each accounting for 18 days. As the trawlers usually land their catches only in the after noons, the time of observation for all selected days is fixed as 1200 to 1800 hours and each day was considered as a single observation day as against the landing centre day already mentioned earlier. Thus we will have 18 days of observation in a month and these 18 days could be considered as a simple random sample from the days in month drawn without replacement. On each selected day a certain number of boats were selected to observe the catch depending upon the number of boats landing (Alagaraja *op.cit)*. Here also it was assumed that the boats were selected without replacement though in practice they were usually selected systematically.

The monthwise number of fishing days (Number of days) and the observed number of days at the Cochin Fisheries Harbour during 1992 and 1993 are given below

Table I.1 *Number of fishing days and number of days observed at Cochin Fisheries Harbour during 1992 and 1993*

	1992			**1993**	
Month	NF	NDS		NF	NDS
January	27	18		26	13
February	25	11		24	16
March	26	16		27	16
April	26	15		24	15
May	26	16		26	12
June	18	9		11	8
July	17	7		23	12
August	26	15		25	15
September	26	14		26	15
October	27	8		26	15
November	25	17		26	13
December	27	15		26	13

(Note: NF is the number of fishing days in a month NDS is the number of days observed)

From the preceding table it is clear that the number of fishing days in month is varying so also the number of days observed. This is due to many reasons such as Sundays and some festival days being fishing holidays and some self imposed closed holidays by the fishermen. Although 18 days per month were selected observations could not be made on some days due to various reasons and only the effective number of days observed were considered for the study.

Ideally one would expect the sampling scheme to be uniform in all the months but due to the peculiar nature of the population being covered the uniformity could not be ensured. However, the evaluation of the sampling scheme would still be valid because the basic structure was not disturbed.

Thus the scheme of collection of catch statistics for the purpose of this study can be assumed to be that of a classical two-stage design with the days forming the first stage units and the boats landing their catches being the second stage units. Let there be N days in a month from which n days are selected at random without replacement. On the ith selected day let M_i be the number of boats landing their catch and mi be the number of boats selected from M_i without replacement for observing the total catch and effort from the each boat. Let C_{ij} be catch observed from the jth sampled boat on the ith selected day. Let $\mathbf{C'}_{i(mi)} = (1/m_i)\sum C_{ij}$ be the average catch per boat on the ith selected day and the estimated total catch per day is given by $M_i \cdot \mathbf{C'}_{i(mi)}$.

The estimated total catch for the month is given by

$$\mathbf{C'}_T = (N/n) \sum(M_i/m_i) \sum C_{ij}$$

$$=(N/n)\sum M_i \mathbf{C'}_{i(mi)}$$

The estimated variance of $\mathbf{C'}_T$ is

$$V(\mathbf{C'}_T) = N^2 \; (v_1 + v_2) \qquad \text{.......... I.3.1.1}$$

where $v_1 = (1/n - 1/N)s^2_b$

$$v_2 = (1/nN) \sum M^2_i(1/m_i - 1/M_i)\, s^2_i$$

$$s^2_b = (1/(n-1)) \sum (M_i\mathbf{C'}_{i(mi)} - C_1)^2$$

$$C_1 = (1/n) \sum M_i\mathbf{C'}_{i(mi)}$$

$$s^2_i = (1/(m_i-1)) \sum(C_{ij} - \mathbf{C'}_{i(mi)})^2$$

This is the classical estimate of variance found in theory of two-stage sampling. The optimum sample size can analytically obtained using the appropriate formulation based on the estimated variations at each stage of sampling. However, strictly in the implementation stage and at selection stage there might be some deviations from the theoretical approach and this may preclude estimation of optimum sample size using the classical formulation. It may be noted in the case study undertaken there is not much of complexity and the computations would be very straightforward. However on a larger scale which is the case with the All India sample survey for fish catch statistics , the calculations could be very complex because the nature of sampling scheme might vary from region to region. So the data from this case study is utilized for demonstrating the usefulness of bootstrap evaluation of the complex sample survey.

I.4 Results

Ideally, the bootstrap evaluation in this case should be carried out in two stages one for the days and the other on the number of boats on the selected day. However, the bootstrap sampling was done only among the first stage units because on analysis it was found the percentage contribution of the variance due to the second stage units to the total variance was not large enough to be considered and the major contribution to the total variance was from among the first stage units only. Based on the variance formula as given in **I.3.1.1** the coefficient of variation in the estimated average catch per day by considering only the first stage units and that by including the second stage units also is summarized in the Table I . 2.

Table I. 2 Percentage coefficient of variation during 1992 and 1993.

	1992		1993	
Month	I	II	I	II
January	5.72	7.77	9.66	12.26
February	12.81	14.52	6.38	7.92
March	6.21	7.59	5.05	5.54
April	4.97	6.95	7.30	8.07
May	10.30	11.74	11.09	11.84
June	14.21	14.69	19.40	19.97
July	38.76	38.86	21.24	21.99
August	11.39	11.95	8.09	9.22
September	10.95	11.45	9.12	10.03
October	9.82	10.66	9.26	10.64
November	13.80	15.26	5.46	7.05
December	11.34	11.91	9.33	11.31

(Note: I denotes C.V. by considering primary stage only and II denotes C.V. by considering both the stages ,.)

From the above table we see that major contribution to the total variance is mainly from variation among the first stage units only and hence for the remainder of the study the variance of the first stage units were only considered and the variance due to the second stage units was ignored. Similar approach was followed by Kutty et.al.(*op.cit.*). Therefore, the bootstrap was done only for the first stage and the C.V. was estimated for different bootstrap sample sizes.

Only those months where the number of observations is more than 8 days were considered for analysis.

Two bootstrap experiments were carried out each with 500 and 1000 bootstraps. The data were analyzed on a PC/AT and the bootstrap software for this study was developed by the investigator himself in C language. The trend in coefficient of variation for different sample sizes starting from sample size of 2 days is depicted in the figures(Fig I.1 to Fig I. 21). From the figures it is observed that the coefficient of variation in most of the months ranged between 10 to 15% for 10 or more days of observation per month. If a precision level of 10 to 15 % for estimating the total landings from a centre to is assumed to be satisfactory, it can be concluded that,in general, 10-12 days observation would be sufficient to estimate the catch statistics.

LIMITATIONS

The conclusions about the optimum number of observations for a desired level of precision cannot obviously, be generalized to all the single centre zones in the country. Besides, these results are applicable only to the trawl fishery of the selected centre and hence same conclusions may not be valid for covering all other types of fisheries such as gillnet, ring-seine , purse-seine fishery. Because of the resource constraint in time and money the investigator could concentrate only on one type fishery which is ofcourse the most dominant and an important fishery.

Another important point to be considered is the fact that the trawl fishery is multispecies in nature, though primarily targetted to exploit the shrimps. It was mentioned that the Central Marine Fisheries Research Institute, cochin provides species / groupwise estimates of landings. Present study aims to study only the trawl fishery in its entirety by considering the total catch and not the individual items of the catch. It may be mentioned here that because of apparent complexity in estimating coefficient of variation itemwise it would be impracticable to advise on sampling schemes for individual species or groups. In conclusion, the following observation of Efron and Tibshirani (*op.cit)* sums up the bootstrap analysis.

Even for relatively simple problems computer intensive methods like bootstrap are an increasingly good data analytic bargain in era of exponentially declining computational costs.

FIG I.1 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - Janaury 1992

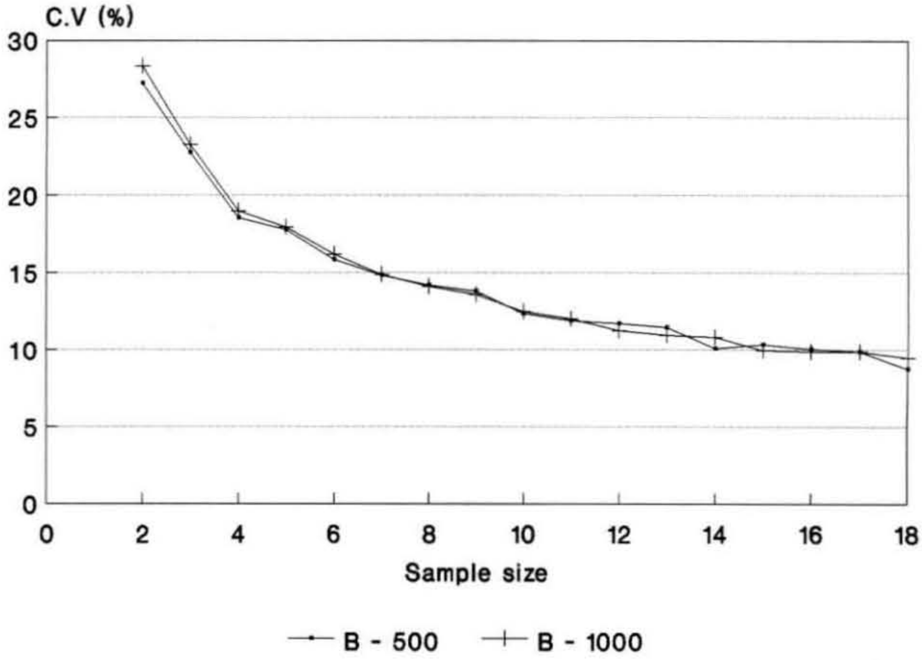


FIG I.2 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - February 1992

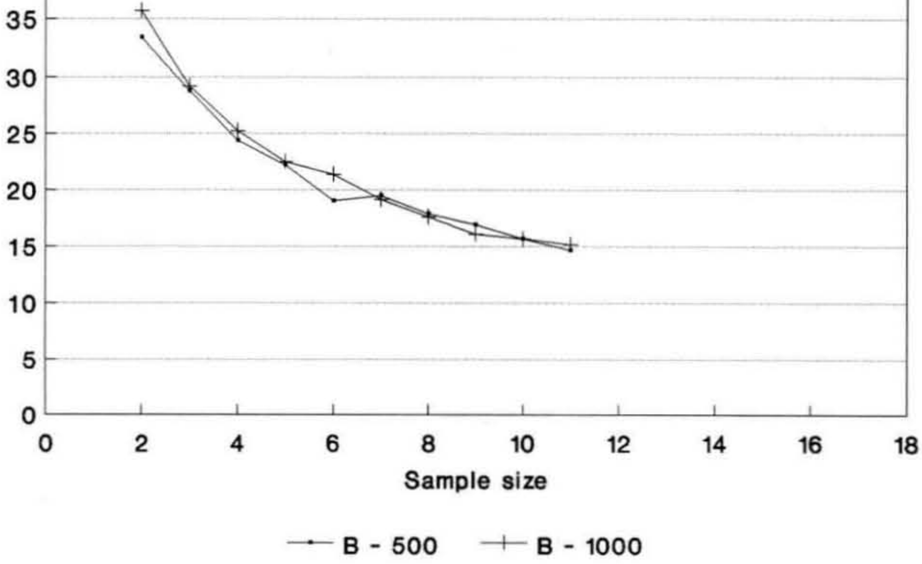


FIG I.3 COEFFICIENT OF VARIATION (%)

Cochin Fisheries Harbour - March 1992

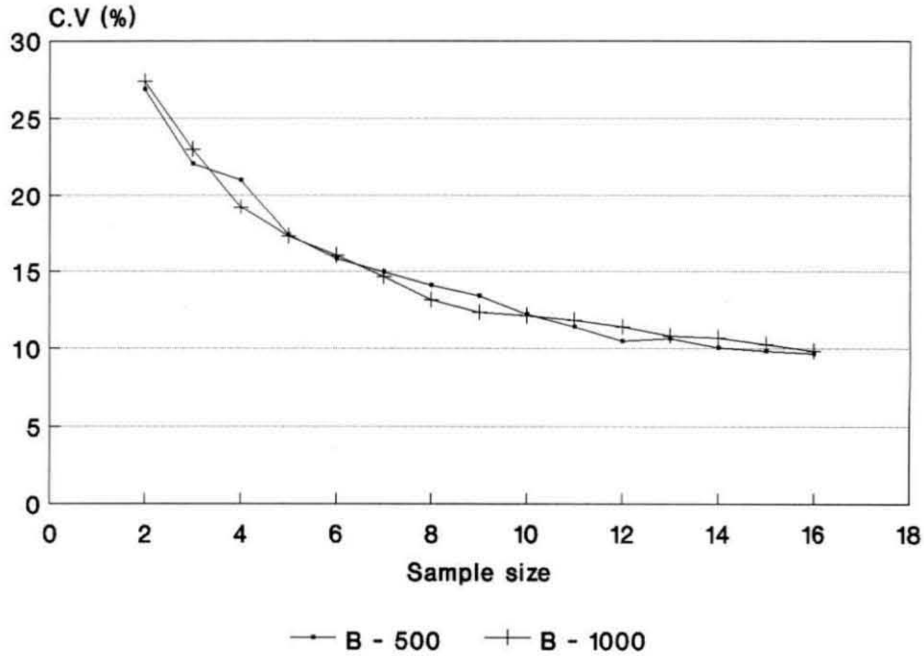


FIG I.4 COEFFICIENT OF VARIATION (%)

Cochin Fisheries Harbour - April 1992

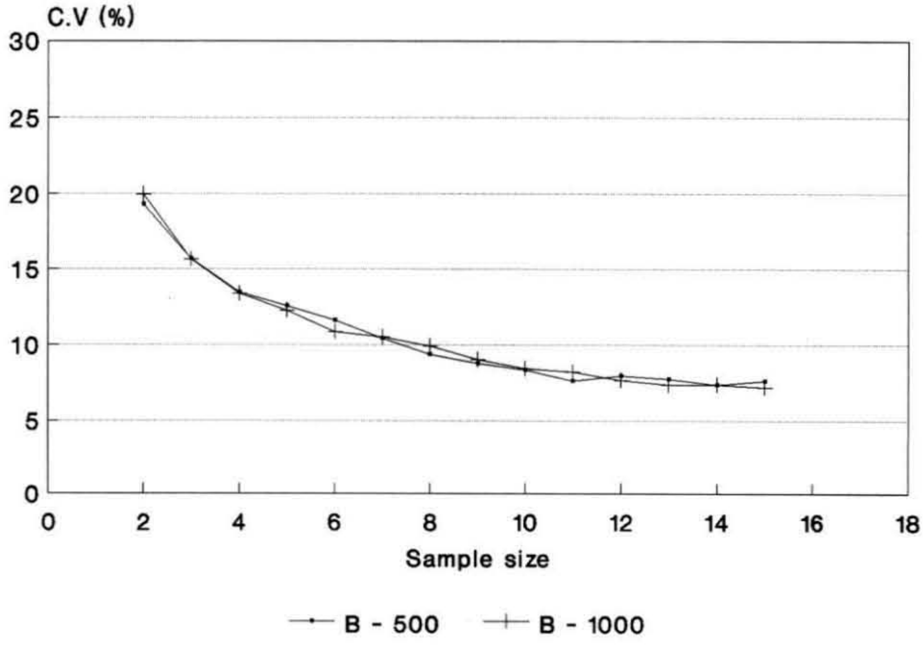


FIG I.5 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - May 1992

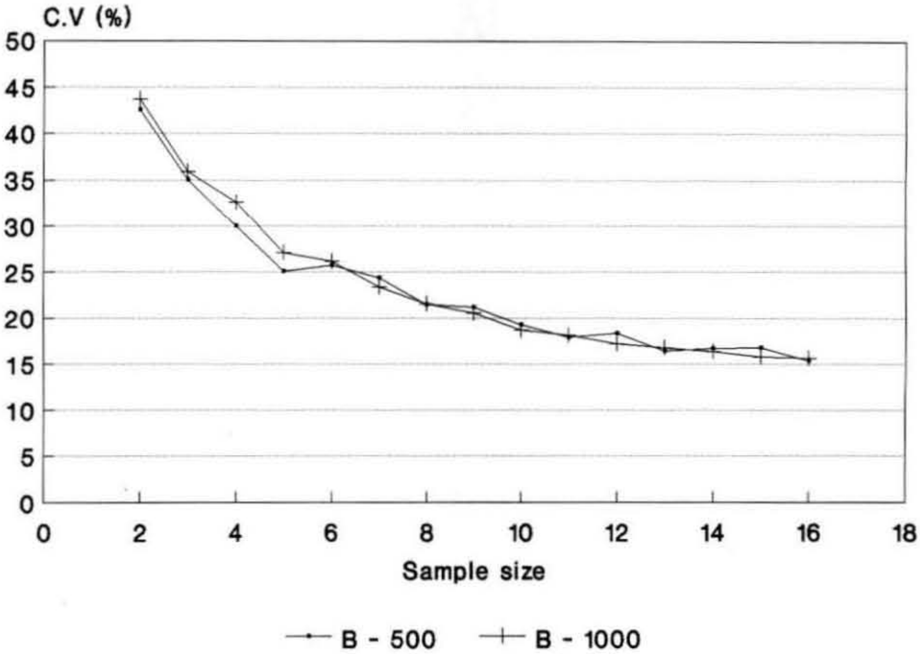


FIG I.6 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - June 1992

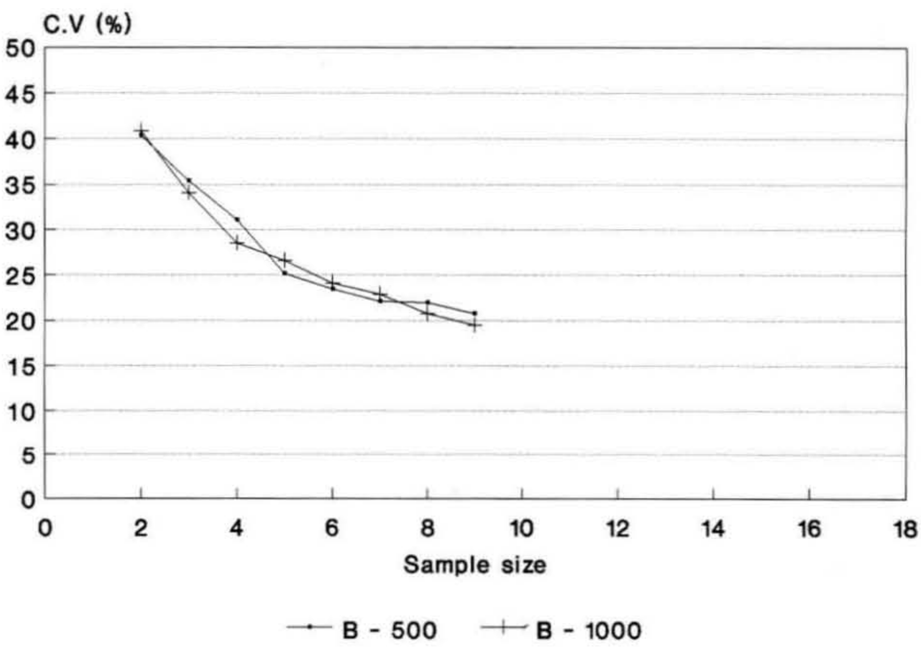


FIG I.7 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - August 1992

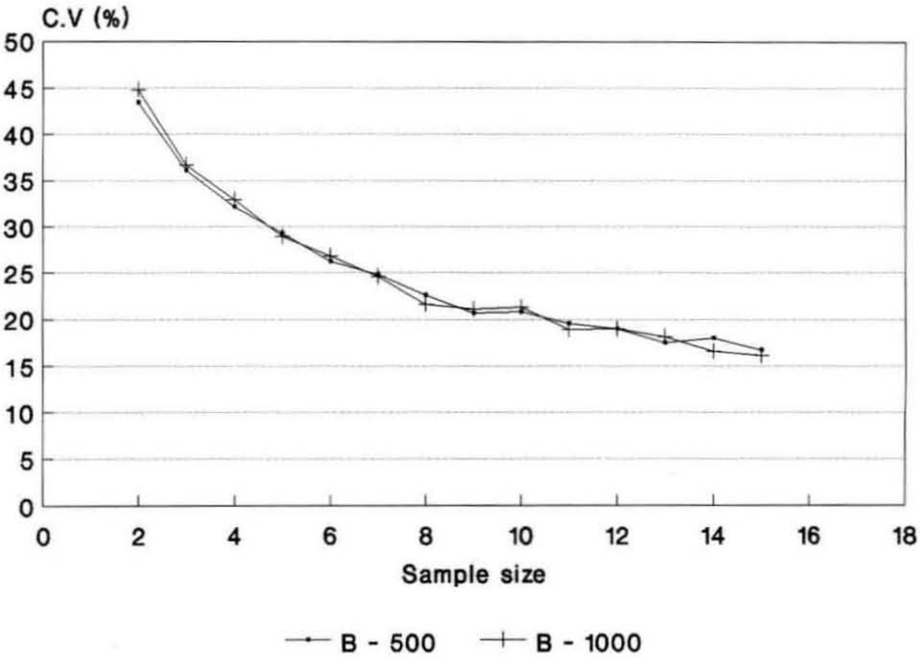


FIG I.8 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour- September 1992

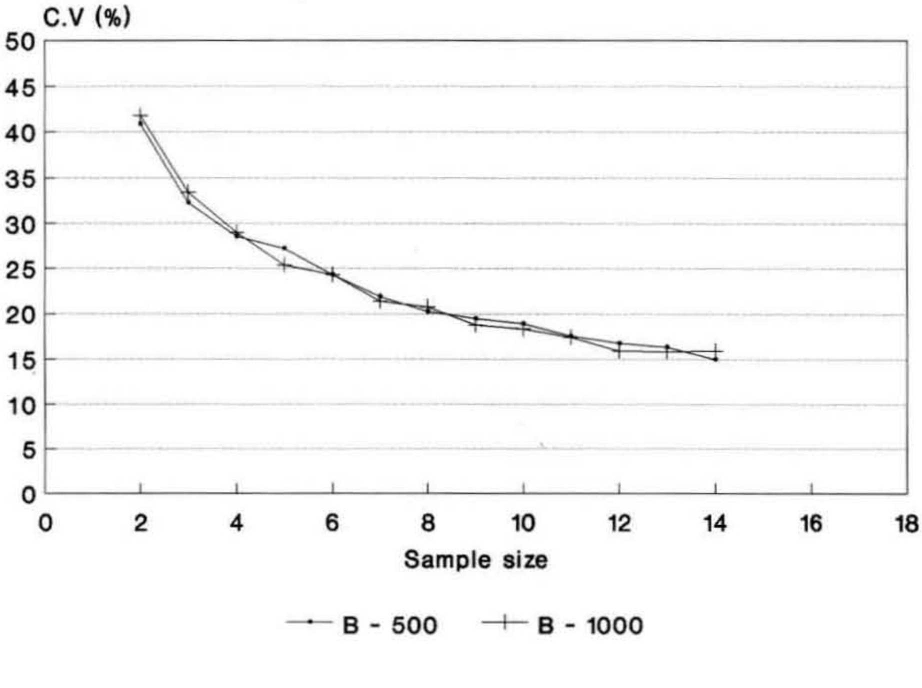


FIG I.9 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - November 1992

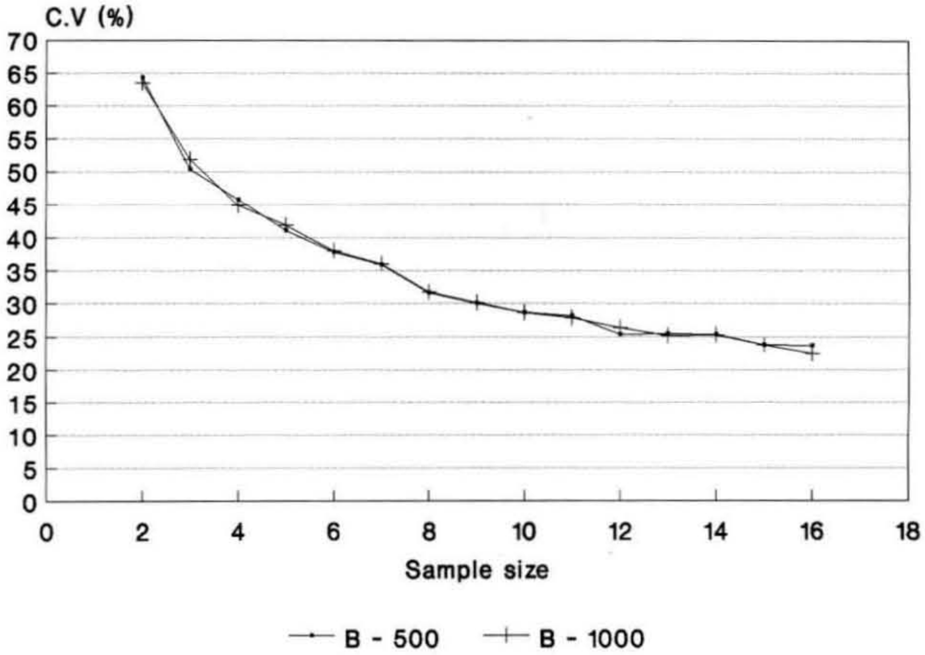


FIG I.10 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - December 1992

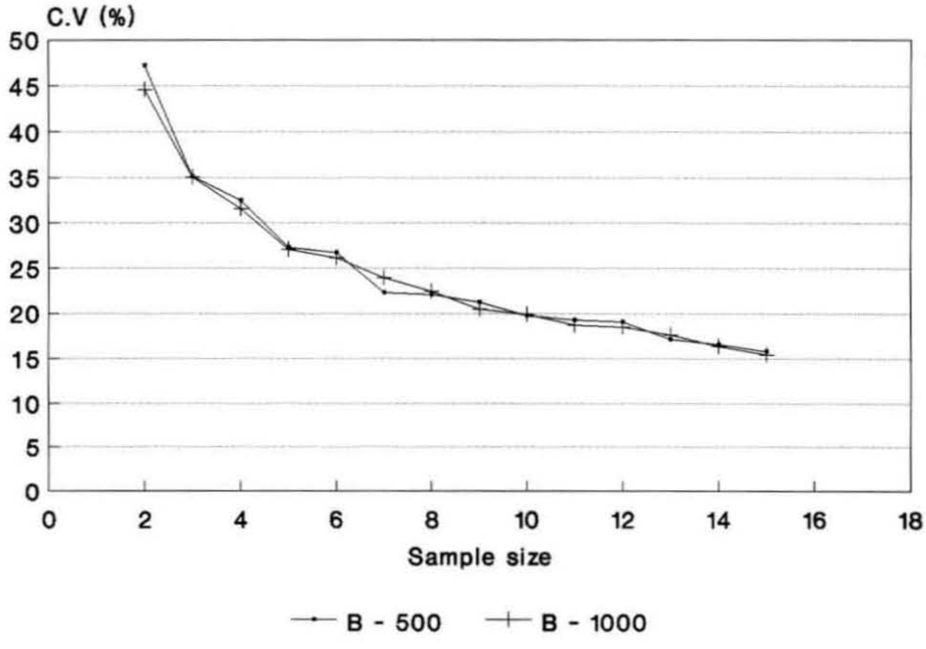


FIG I.11 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - January 1993

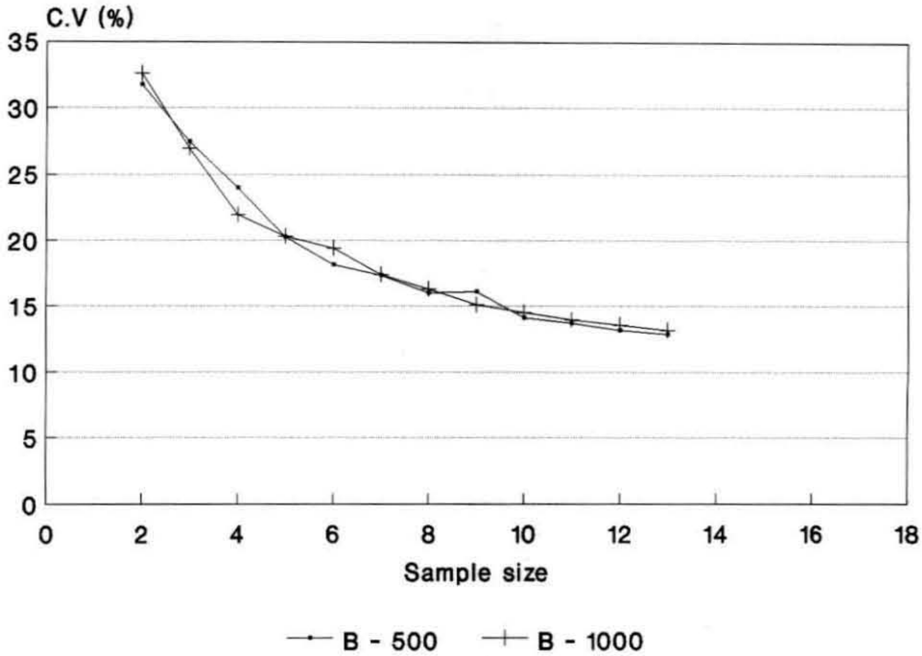


FIG I.12 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - February 1993

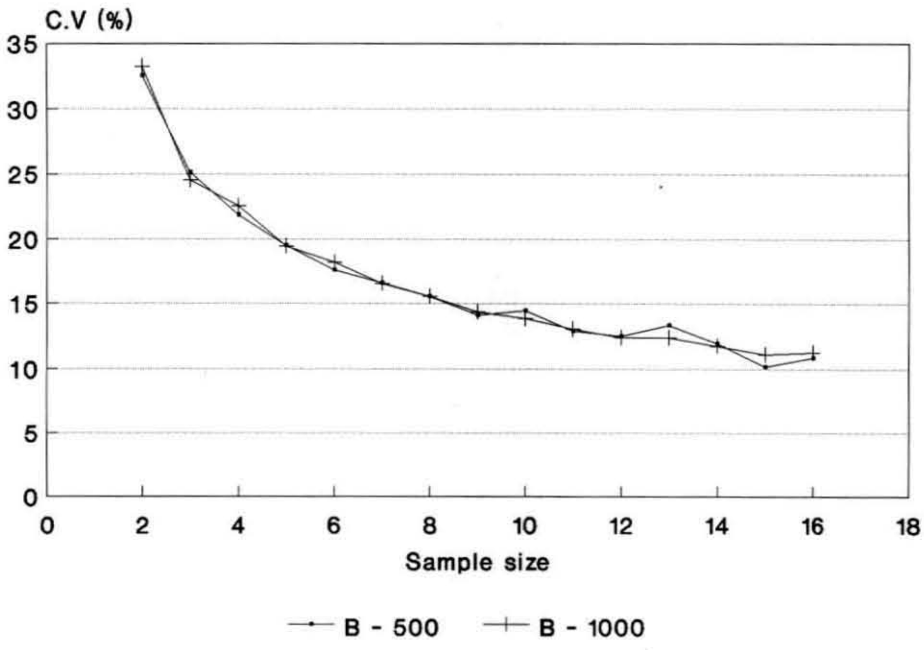


FIG I.13 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - March 1993

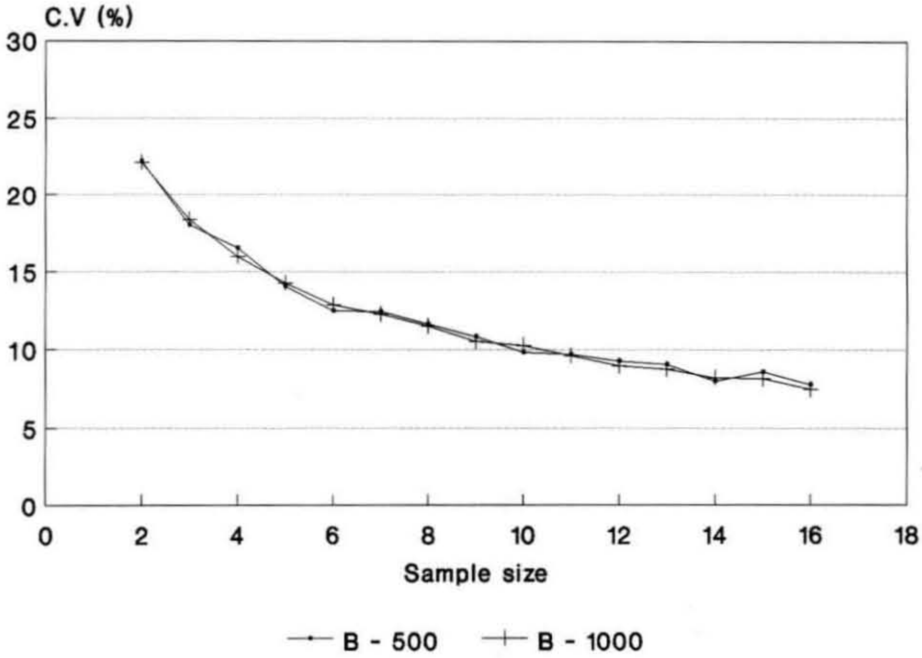


FIG I.14 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - April 1993

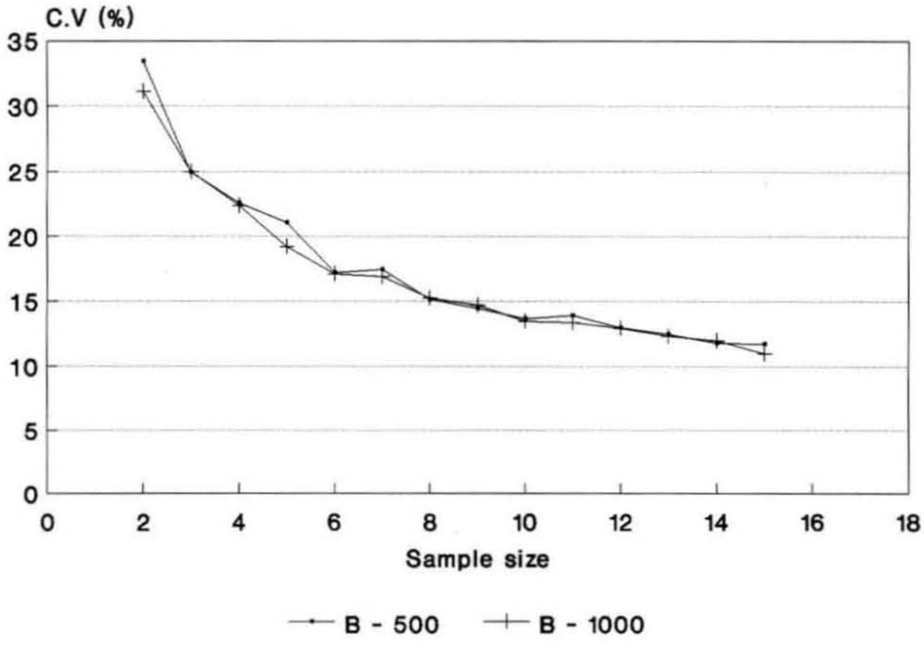


FIG I.15 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - May 1993

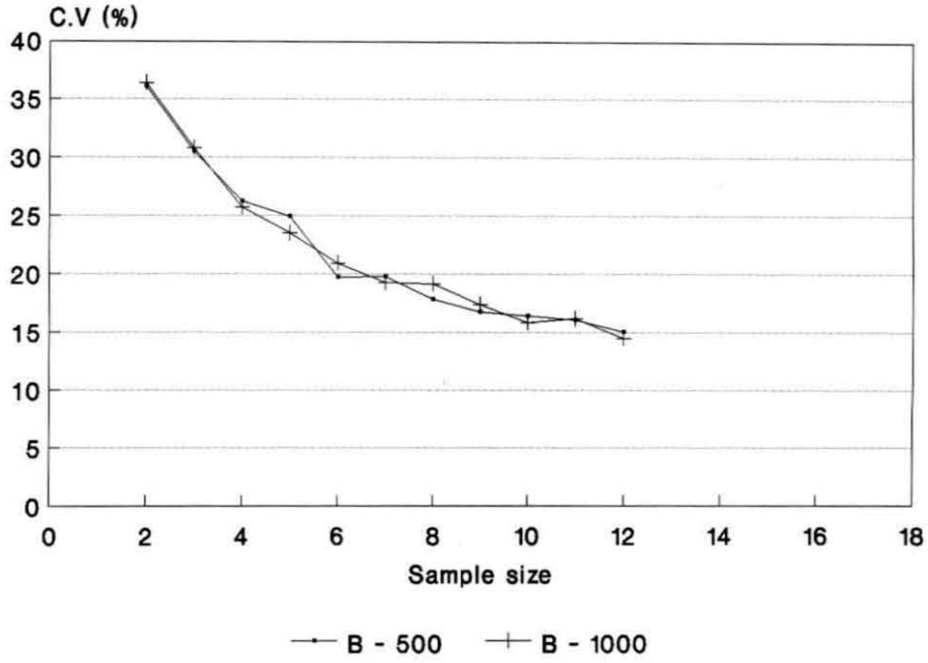


FIG I.16 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - July 1993

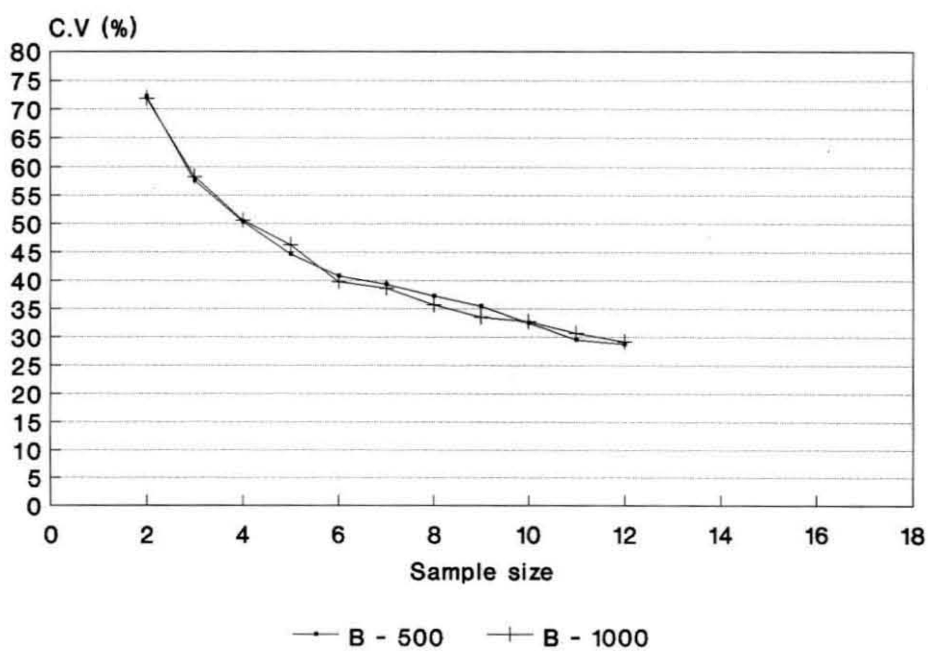


FIG I.17 COEFFICIENT OF VARIATION (%)

Cochin Fisheries Harbour - August 1993

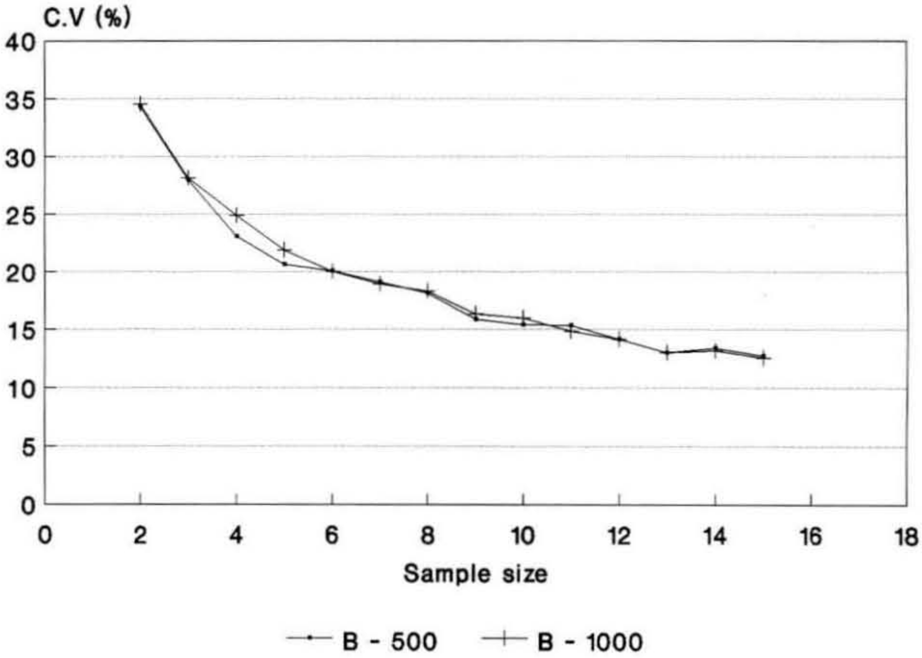


FIG I.18 COEFFICIENT OF VARIATION (%)

Cochin Fisheries Harbour-September 1993

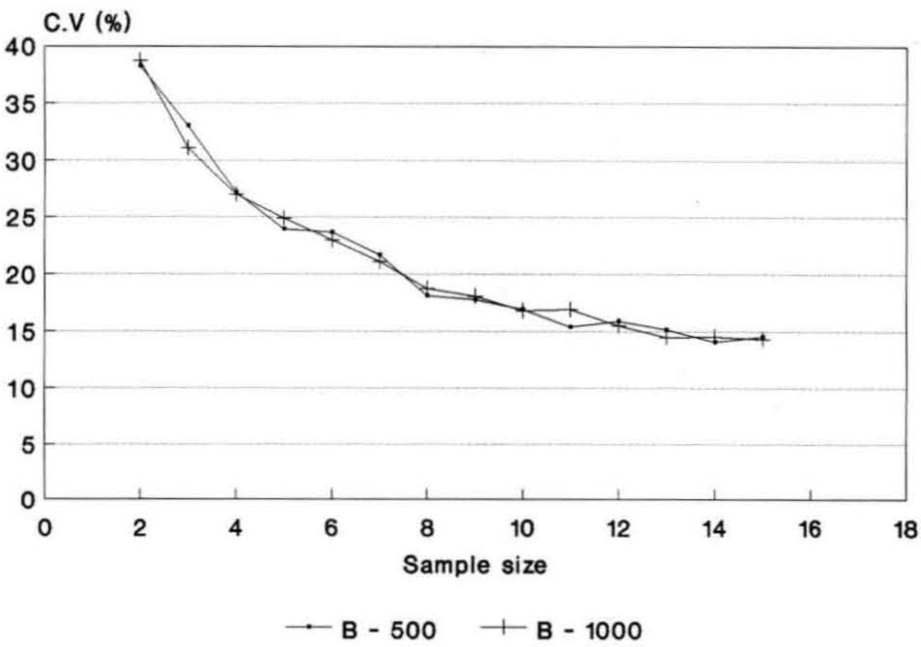


FIG I.19 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour-October 1993

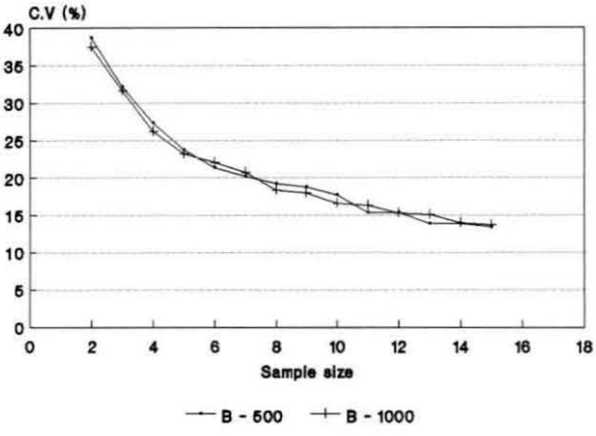


FIG I.20 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour-November 1993

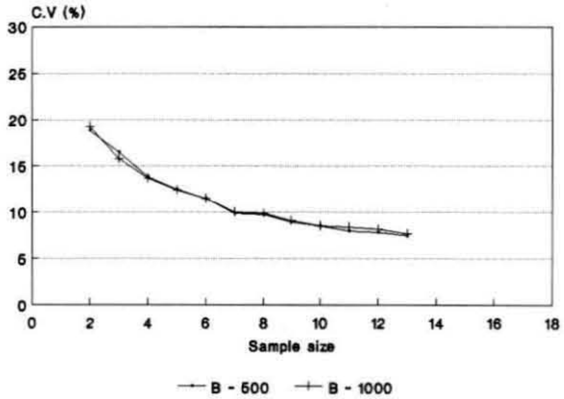
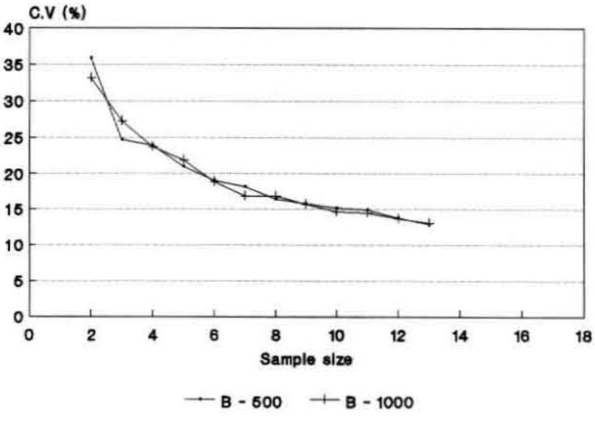


FIG I.21 COEFFICIENT OF VARIATION (%)
Cochin Fisheries Harbour - December 1993



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CHAPTER II

CHAPTER II

EVALUATION OF THE SCHAEFER'S PRODUCTION MODEL

II.1 Introduction

In fish stock assessment there are two types of models that are employed to study the dynamics of the fish stocks. One is the micro or analytical models (or methods) and the other the macro or global (surplus production) models. Models that can be solved in closed form mathematically are analytical models. For such models a general solution can be obtained which is applicable to all situations the model can represent. In analytical models we take into consideration the various components that affect the stock, namely, growth, mortality, size or age at capture etc. In macro models we deal with only the observable inputs (say fishing effort) and the actual ouputs (yield in weight) from a given population. The main features which attract the fishery biologist to use these models are (i) they are simple models (ii) the data requirements are limited and (iii) computational ease in estimating the modal parameters.

To assess the status of the stock or the effect of fishing (exploitation) on it we can proceed in two ways. The first consists of examining and evaluating each term and formulating equations for the behaviour of each term and their effect singly or in combination on the stock. This approach comes under the purview of already mentioned analytical models (or methods). These require a detailed study of the stock and data requirements will be large.

The second approach would be to study the overall effect of all factors that control the biomass simultaneously i.e. $\Delta B = B_1 - B_0$ and to evaluate how ΔB behaves as function of biomass B, where B_0 and B_1 are the biomass at the beginning and end of the year. The other factors that should be considered besides the natural growth (ΔB) are the fishing effort (rate of fishing) and catch or yield Y. Surplus production models or macro or global models take account of this approach.

II.2 REVIEW

II.2. 1 Surplus Production Models

A conceptual framework of surplus production models is presented on the basis of which the derived models are built.

In the absence of exploitation it is generally assumed that the total biomass of stock will not exceed beyond some limiting size. This is constrained by the carrying capacity of the ecosystem of which the stock is a part. At the limiting value of the biomass the rate of change in biomass will be zero. It is assumed that the rate at which it approaches its limiting value is a function of the biomass. That is the instantaneous rate of change in biomass (1/B).(dB/dt) is a decreasing function of the biomass.

$$(1/B).(dB/dt) = f(B)$$

and at $B = B_{\infty}$ (limiting size or asymptotic value) $dB/dt = 0$.

In exploited stock, catches reduce the total biomass. The biomass of the exploited stock thus depends on the size (quantity) of catches. If the rate of removal is higher than the stock's natural rate of growth the biomass will decrease, otherwise, the biomass will increase but rather slowly than it would in the absence of fishing. The stock is said to be in equilibrium state if the natural rate of natural growth equals the removals by fishing. This catch is termed as the *equilibrium catch*. From the fishery management point of view taking equilibrium catch will be desirable since it maintains the biomass at a constant level. The maximum equilibrium catch (or the Maximum Sustainable Yield - MSY) can be taken at an intermediate level when the absolute rate of natural rate of growth is highest. In a fishery the net rate of production equals gross rate of production minus the rate of removals from the population

$$\text{i.e. } (1/B).(dB/dt) = f(B) - F$$

For a given time interval Δt assuming that F remains constant we get,

$$(1/B).(\Delta B/\Delta t) = f(\mathbf{B}) - F$$

where **B** is the mean biomass during Δt.

From this we get the change in biomass ΔB as

$$\Delta B = f(B).\mathbf{B}.\ \Delta t - F.\mathbf{B}.\ \Delta t$$

At equilibruim $\Delta B = 0$, so we get, $F = f(\mathbf{B})$ (rate of removals is a function of biomass)

We Know that F = Y/B and that in equilibrium,

$$Ye = F.\mathbf{B}.\ \Delta t = \mathbf{B}.f(\mathbf{B}).\ \Delta t \text{ , and assuming } \Delta t = 1$$

$Ye = \mathbf{B}.f(\mathbf{B})$ and in terms of F it can written as

$Ye = F.f(F)$, where Ye is the equilibrium yield.

The above equations are fundamental to the assessment of a fishery and they can be expressed in terms of indices of biomass and fishing effort. Let f be the fishing effort during time Δt (assumed to be constant during the time interval) and related to F as $F = q.f$ where q is the catchability coefficient.

The index of mean biomass during Δt or during a year (taking $\Delta t=1$) is obtained from $Y = q.f.B$ and $Y/f = U = q.B$ where U is the catch per unit of effort and considered here as an index of abundance.

The basic assumptions involved in surplus production models are

(i) We are dealing with a unit stock.

(ii) The population reacts instantaneously to any change in effort

(iii) The stock is in equilibrium.

II .2.2Schaefer' model

Schaefer(1954) has assumed that the specific rate of natural growth f(B) is a decreasing function of biomass B and the relationship to be linear,

$$f(B) = r - (r/k)B$$

when the biomass has reached its maximum level (asymptotic size) B_∞ then f(B) = 0. where r is the intrinsic rate of growth and k the carrying capacity.

$$0 = r - (r/k).B_\infty \quad \text{and } r = (r/k).\ B_\infty$$

thus we have $f(B) = (r/k)(\ B_\infty - B)$

in equilibrim condition

$$f(B) = K(B_\infty\ - \mathbf{B}) \text{ where } \mathbf{B} \text{ is the mean biomass}$$

and $\quad Ye = \mathbf{B}.\ \mathbf{f(B)}$

$$=(r/k).\mathbf{B}.(\ B_\infty\ - \mathbf{B})$$

$$\text{or , } Ye = F(B_\infty\ - kF/r)$$

This can be converted interms of effort(f) and catch per unit effort (U) and can be written as

$$Ye = a.f - b.f^2$$

$$U = a - b.f \quad \text{...........} \quad \text{II.2 .1}$$

where a and b are constants to be estimated.

From the above equations we get

Maximum Sustainbale Yield (MSY) $= Y_{max} = a^2 / 4b$

$f_{MSY} = a/2b$ the fishing effort required to get MSY

$U_{max} = a/2$

In practice, the equation $U = a - b.f$ is basic to assessment of a stock and a fishery. From this we get estimates of catch as a function of effort. Thus these equations help us to estimate MSY, the corresponding level of fishing effort, the equilibrium catches that we can expect at other levels of effort and the relative abundance of stock..

Research on suplus production models is mainly devoted to (1) model formulation (2) parameter estimation (3) extension to multispecies or multifleet fisheries and (4) introduction of environmental information.

Schnute(1977) recast the Schaefer's model into a stochastic dynamic model. Because random errors were shown explicitly the parameter estimation for model was dictated by the least squares condition. The model was converted into a form directly applicable to a data stream of annual fishing effort and catches. The new version was also stochastic. Equations were given for predicting next year's catch. Agnello and Anderson(1977),Pope (1980) and Prager(1994) proposed theoretical extensions of Schaefer model.

Tsoa *et.al* (1985) genaralised the conventional Schaefer model to permit estimation of unconstrained Cobb-Douglas production function for a fishery in the absence of population data.

Galto and Rinaldi(1980) proposed a commercial fishery production model which is given by

$$C_{t+1}= a(1-\exp(-qE_{t+1})) + b((1-x_2)/(1-x_1)).\exp(-x_1).C_t$$

$$- c\,((1-x_2)/(1-x_1)^2)(\exp(-x_1))^2\, C_t^2$$

where C_t and C_{t+1} are the catches at times t and t+1,

E_t and E_{t+1} are the efforts at times t and t+1

$x_1= \exp(-qE_t)$ and $x_2= \exp(-qE_{t+1})$

q is the catchability quotient ; a,b and c are constants to be estimated

Roff(1983) proposed the following empirical model

$$C_{t+1} = A + B\ E_{t+1}\ C_t/E_t$$

He compared this auto-regressive model with the Deriso delay diffrential model and Schnute's version of Schaefer model. He found that for the demersal fish stocks this model was found to fit the data better. He could not however, ascribe any biological significance to the model.

Alagaraja(1984) proposed a simple model in which the differences in the catches of successive years are depicted as functions of previous year's catch and termed it as Relative Response Model. A suitable relationship needs to be worked out depending upon the data. The simplest being $C_{t+1} = a + b\ C_t$, which is nothing but the autoregressiive model of order 1.

Srinath(1992) dealt with some problems associated with fitting surplus production models to unsuitable data. He contended that purely empirical models would fit the data better than the conventional surplus production models and proposed the following catch(C) - effort(E) relationship

$C = a.\ E^{b1} \exp(-b_2.E)$ to describe the fishery.

II .2.3 Model fitting

To fit the above models we require a series of catch and effort data over a period of time. If we assume that catches correspond to the equilibrium catches we can proceed strightaway with the estimation of MSY and fMSY by fitting the data to the models through standard regression techniques. Choice of the model depends upon the type of relationship of effort with the catch rate and of course the goodness of fit criterion employed. Ricker(1975) has recommended an alternative method of fitting the data through application of functional regression analysis. Gulland (1983) adviced fitting a curve by eye helps one to make use of prior experience and knowledge of the fishery.

Procedures for estimating the parameters of the model were first proposed by Schaefer(1954 & 1957). Fox (1975) proposed a general production fitting algorithm PRODFIT. Walter(1975) proposed a graphical method of calculating coefficients for a Schaefer model by plotting the catch per unit effort against the fishing effort and corrected the values for disequilibrium of the fishery using certain approximations. Tools for estimating parameters were also provided by Pella and Tomlinson (1969), Schnute(*op.cit.*), Ludwig and Walters(1989) and Polacheck *et.al.*(1993). McGaw(1980) found out the confidence intervals using the Fieller's method for the effort at maximum sustainable yield. However, he could not obtain the same for the maximum sustainable yield because it was derived from non-linear combinations of parameters.

There are several ways of fitting surplus production models,however, only three have been widely used. They are (1) effort averaging method (Gulland, 1983; Fox, .1975) (2) process error estimators (Schnute, *op.cit.*) and (3) observation error estimators(Pella and Tomlinson, *op.cit.*; Ludwig and Walters, *op.cit.*).

The observation error criterion depends on the error function in the catch and assumes that the stock or population equation is determinstic. Whereas in the process error method , it is assumed that the errors are due to population size.

Uhler(1980) examined analytically the least squares regression estimates of the Schaefer's model and made some Monte Carlo simulations to evaluate some alternative forms of the Schaefer's model. He observed the estimates of the parameters of the models were sensitive to the random errors in the models.

Ludwig and Walters(*op.cit.*) compared various estimation procedures based on their accuracy of estimating the optimal effort. They tested the models using a procedure in which they assumed equal variances for process and observation erors. They simulated a stock with different initial stock sizes and effort patterns, using the random sequences of process and observation errors. Their analysis revealed that Deriso-Schnute scheme was inferior to Ricker's stock-production model. They contended that for catch and effort data with large errors and/or low variations in stock size and effort one was committed to give up fidelity of the esimation model to the underlying dynamics in order to improve estimation performance.

Polacheck *et.al.* (*op.cit.*) compared the three approaches to fit surplus production model using real and simulated data and concluded that they yielded substantially different interpretations of productivity. They further concluded that the effort averaging method would almost always produced what appeared to be reasonable estimates of maximum sustainable yield and the optimum effort and the r^2 - statistic used to evaluate the goodness of fit could provide an unrealistic illusion of confidence about the parameter estimates obtained. Process error estimators produced much less reliable estimates than the observation error estimators. They found that observation error method produced lower estimates of maximum sustainable yield and optimum effort and were the least biased. They recommended that observation error estimators be used while fitting surplus production models.

Laloe (1995) made a critical review of the surplus production models and observed that although the precision of some parameter estimators may appear to be good, the strong asymmetry of confidence intervals and the large impact of the choice of a given formula on a given formula went against that feeling. Fishing effort standardisation did not lead necessarily to useful results for management. He also concluded that observation error estimators gave better results though he did not advocate it as the only approach as was done by Polacheck *et.al.* (*op.cit.*). He observed that the possible progress in the use of surplus production models was more likely to concern the quality of questions that should be observed rather than the respond to usual questions. He concluded that surplus production models should be used in framework in order to give representations of fisheries taking into account "expert knowledge" as well as a greater set of information.

II .3 Alternative formulation of schaefer model

One cannot assess the quality of an estimation procedure unless one is sure of the nature of the model formulation and of the distrubution of the errors. The ability to choose between different formulations is thus important from both a biological and estimation point of view. The new formulations could only be interest if they might accept additional information on the fishing activity or on some environmental parameters or on other sources of errors.

Let us now see some alternate forms of the Schaefer's model and examine how these forms perform under random perturbations. We recall the Schaefer's model in its continuous form as

$$(1/B).dB/dt= r -(r/k)B -C$$

$$C = q.f.B$$

$$U=(C/f)=q.B$$

Usually, the fitting of the model and estimation of the parmeters are made by employing the equation II.2.1 by least squares method by incorporating an stochastic error term. The basic equation is considered to be a deterministic one and still at the estimation stage a stochastic term is introduced. Here we will consider introduction of stochastic error terms in the above set of equations and examine how the estimates of the parameters and also the estimates of parameters for mangagement policy behave under different levels of perturbation terms.

Here an attempt is made to compare the performance of two formulations of Schaefer's model one discrete and another a continuous form (Uhler ,op.cit.) in respect of the model parameters and hence the management related estimates of maximum sustainable yield and the corresponding effort, using the simulation techniques.

Although the Schaefer's model is too simple to describe and explain a complex dynamic fishery, it can often be considered as an approximation. In this study an attempt has been made to examine the characterstics of the Schaefer's model by constructing a simulated model(with the help of a computer) which mimics the dynamics of a real fishery and then use it to generate catch and effort data for estimating the parameters of the population. A stochastic error component has been introduced in the stock and catch generating processs. According to Ludwig and Walters (op.cit.) fisheries data are often "noisy" because of inadequacy of sampling or effects of biophysical factors other than stock size and fishing effort. Bootstrap technique (Efron and Tibshirani ,1986) was employed to estimate the bias of the estimates of the parameters of the Schaefer's model. The perfomance of Schaefer's model has been studied both in its continuous form and the discrete form. It is worth mentioning here that simulation modelling allows researchers to explore alternative hypotheses about relationships within a system and to generate a variety of experiments before choosing experiments that will be conducted in the real systems. Simulation is the process of using a model to mimic, or trace through step by step, the behaviour of the systemd we are studying(Grant 1986). Concepts of the state of the system and the change of state of the system are fundemental to simulation. According to Grant(op.cit.) model use within a management framework implies effective communication of model results to those managers and policy makers whose decisions ultimately impact wildlife and fisheries resources.

The basic Schaefer's model in its discrete form can be written as

$$B_{t+1} - B_t = rB_t - (r/k)B_t^2 - C_t \quad \text{(Growth equation)} \quad \ldots \text{II.3.1}$$

$$C_t = qf_tB_t \quad \text{(Catch process)} \quad \ldots \text{II.3.2}$$

$$U_t = C_t/f_t \quad \ldots \text{II.3.3}$$

Let us now introduce the stochastic error component in the growth equation and the catch process. This is in conformity with that of earlier mentioned workers who termed them as "process errors" and "observation errors". By this we assume that both the stock size and the catch are subject to random processess. This can be a realistic assumption in the context of dynamic environment in which the stock lives. Thus we have

$$B_{t+1} - B_t = rB_t - (r/k)B_t^2 - C_t + \varepsilon_t \quad \text{... II.3.4}$$

$$C_t = qf_tB_t + \phi_t \quad \text{... II.3.5}$$

Here it is assumed that ε_t and ϕ_t are independently normally distributed random variables with zero means and constant variances σ_1^2 and σ_2^2.

Now, we get,

$$(B_{t+1} - B_t)/B_t = r - (r/k)B_t - qf_t + \varepsilon'_t \quad \text{..... II.3.6}$$

(This is obtained by dividing (A) by (B) and taking $\varepsilon'_t = (\varepsilon_t - \phi_t)/B_t$)

Since B_t, the stock biomass is not known the observable proxy for it namely, U_t the catch per unit effort can be used to build the equation.

$$U_t = qf_t + \phi'_t \quad \text{... II.3.7}$$

where $\phi_t' = \phi_t / f_t$

Substituting this in the above equation and after rearranging we get

$$(U_{t+1}/U_t) = a_1 + a_2U_t + a_3f_t + \theta_t \quad \text{... II.3.8 (model } \mathbf{A}\text{)}$$

where $a_1 = (1+r)$; $a_2 = -(r/kq)$ and $a_3 = -q$

and $\theta_t = f(U_t, \varepsilon_t, \phi_t)$

Since U_t and the error term are correlated any attempt to estimate the above equation by the ordinary least squares will produce biased estimates(Uhler, *op.cit*).

The continuous form of the Schaefer's model is given by

$$dB_t/dt = rB_t - (r/k)B_t^2 - C_t + \delta_t \quad \text{... II.3.9}$$

$$C_t = qf_tB_t + \eta_t \quad \text{... II.3.10}$$

$$U_t = C_t/f_t = qB_t + \eta_t' \quad \text{... II. 3.11}$$

Substituting C_t in the first equation and integrating over

(t,t+1) we get,

$$\log(B_{t+1}/B_t) = r - (r/k)\mathbf{B}_t - q\mathbf{f}_t + \zeta_t' \quad \text{... II.3.12}$$

where $\mathbf{B}_t$ and $\mathbf{f}_t$ are the average biomass and effort in the interval (t,t+1)

$$\text{where } \zeta_t' = \int_t^{t+1} (\delta_t - \eta_t) B_t \, dt$$

Since B_t is unobservable we can express the above equation in terms of U_t as follows

$$\log(U_{t+1}/U_t) = b_1 + b_2\mathbf{U}_t + b_3\mathbf{f}_t + p_t \quad \text{.... II.3.13}$$

where $p_t = f(U_t, f_t, \zeta_t')$ and $b_1 = r$, $b_2 = -r/k$; $b_3 = -q$

It may be noted here that MSY = r.k/4 and f_{msy} = 0.5.r.q

$\mathbf{U}_t$ and $\mathbf{f}_t$ are the time averages and can be considered as the catch per unit effort and the effort during the year.

Since U_t and U_{t+1} are the instantaneous rates they are not usually observed and hence following the approximation of Schnute (*op.cit.*) where $\mathbf{U}_t = \sqrt{(U_t U_{t+1})}$ and we have

$$\log(\mathbf{U}_{t+1}/\mathbf{U}_t) = b_1 + b_2(\mathbf{U}_{t+1} + \mathbf{U}_t)/2 + b_3(\mathbf{f}_{t+1} + \mathbf{f}_t)/2 + \mathbf{p}_t \quad \ldots \text{II.3.14}$$

(model **B**)

where $\mathbf{p}_t = (p_{t+1} + p_t)/2$

Both the models A & B have auto-correlated error terms and application of ordinary least squares will result in biased estimates of r,k and q. Analytically it may not be possible to compare these two models and hence a boot strap evaluation was made by first generating a population series and a catch series with different error levels for the stock and the catch. The population was generated using the discrete time version of the Schaefer's model with the following inputs r=0.45; k=1500 q= 0.000254 for error levels σ_1 =0,25,50,75,100 and σ_2 = 0,10,20,30,40 with initial value of the stock biomass B_o = 1000.

The effort data used to generate the catch was taken from Miyabe (1989). The data was generated for 36 values of effort. The data was simulated for all the 25 combinations of the error terms. The reference date set is the one with 0 level of error term.

The bootstrap regression as suggested by Wu(1986) was used to estimate the parameters and the biases. The number of bootstraps is 1000. The bootstrap estimates of relative bias in r,k,q, msy and fmsy and the estimated coefficient of variation in r, K and q are given tables. The bootstrap relative bias in this case is given by

$$(x - x_0)*100/x_0$$

where x is the average bootstrap estimate (mean over number of bootstrap samples) and x_0 is the value of the parameter. The coefficient of variation is computed as bootstrap standard deviation of the estimate divided by the bootstrap estimate of the parameter multiplied by 100.

II. 4 Results

The bootstrap estimates of relative bias in the estimates of parameters r,k,q (prefixed as 'bias') along with the coeeficient of variation (prefixed as 'cv') and those of the estimates of MSY and f_{MSY} are presented in Tables II.1 to II.6.

Table II .1 *Relative bias in estimates for error in catch equation is 0*

(The first row heading is the error levels in the stock equation)

	0		25		50		75		100	
	A	B	A	B	A	B	A	B	A	B
biasr	0	2.79	42.86	28.68	3.21	-29.35	70.88	-4.54	9.88	-46.99
biask	0	-12.00	-16.13	-6.20	88.40	175.00	-51.87	46.60	0.07	184.07
biasq	0	4.84	18.36	19.24	-17.56	-7.36	140.20	66.40	18.24	-9.32
cvr	0	3.13	12.54	22.82	30.20	51.25	22.80	43.16	25.38	46.09
cvk	0	3.11	13.75	63.04	141.00	305.23	25.48	390.45	44.90	264.75
cvq	0	2.92	15.04	22.67	46.57	46.76	21.97	39.79	30.51	48.26

Table II.2 *Relative bias in estimates for error in catch equation is 10*

(The first row heading is the error levels in the stock equation)

	0		25		50		75		100	
	A	B	A	B	A	B	A	B	A	B
biasr	182.57	26.06	430.57	307.88	141.04	-16.99	203.06	119.70	118.57	32.83
biask	-56.86	258.66	-78.13	-13.80	-4.70	354.00	-55.00	-24.40	115.20	71.40
biasq	155.50	91.04	441.56	332.04	110.16	-8.40	289.32	249.44	63.84	114.36
cvr	13.03	52.68	28.94	47.24	17.63	61.74	46.79	70.40	25.55	50.82
cvk	34.21	1314.7	41.77	538.75	45.53	634.50	125.15	272.81	505.50	323.38
cvq	29.85	47.05	36.19	49.11	34.92	66.59	54.71	67.20	65.38	51.98

Table II.3 *Relative bias in estimates for error in catch equation is 20*

(The first row heading is the error levels in the stock equation)

	0		25		50		75		100	
	A	B	A	B	A	B	A	B	A	B
biasr	536.91	169.46	252.74	5.04	243.51	39.72	554.28	106.20	332.86	123.04
biask	-78.47	44.07	-71.13	443.00	-71.53	57.93	-48.13	74.47	-76.47	-43.47
biasq	699.72	392.80	330.16	55.00	319.84	159.48	828.84	390.32	636.40	375.92
cvr	33.14	53.39	17.16	63.16	16.15	40.86	51.18	81.59	30.91	39.31
cvk	120.12	1033.0	35.88	888.95	40.28	285.18	406.40	657.24	154.39	275.00
cvq	49.44	54.07	30.36	72.31	30.76	58.91	69.70	78.01	40.84	47.11

Table II.4 *Relative bias in estimates for error in catch equation is 30*

(The first row heading is the error levels in the stock equation)

	0		25		50		75		100	
	A	B	A	B	A	B	A	B	A	B
biasr	171.67	5.46	1262.00	131.83	1214.10	212.95	2997.00	448.00	388.48	71.92
biask	1.07	370.07	-88.07	187.80	-71.67	-48.20	-76.20	116.70	-53.07	193.40
biasq	154.00	48.68	2185.10	564.56	2352.70	674.60	6387.00	1063.00	372.20	211.52
cvr	24.88	71.02	53.49	62.93	56.97	55.29	69.72	61.79	30.16	62.03
cvk	221.83	490.28	154.75	371.34	698.30	187.51	737.53	913.57	393.32	577.64
cvq	64.17	83.56	64.29	64.71	66.94	60.11	77.17	64.22	53.78	68.22

Table II.5 *Relative bias in estimates for error in catch equation is 40*

(The first row heading is the error levels in the stock equation)

	0		25		50		75		100	
	A	B	A	B	A	B	A	B	A	B
biasr	668.77	200.15	431.80	81.43	1100.00	175.89	903.60	176.58	593.10	165.07
biask	-86.50	-28.60	-55.60	61.30	-68.40	55.60	-90.60	-28.20	-23.20	-10.60
biasq	1490.70	570.52	617.44	221.56	2440.00	629.40	228.30	599.00	1125.00	429.32
cvr	43.08	60.97	33.98	53.10	74.13	49.90	32.46	66.31	48.65	48.85
cvk	126.60	349.57	678.55	387.70	380.55	572.45	57.44	259.97	1451.40	381.80
cvq	45.18	58.93	49.03	79.19	81.55	69.14	43.45	75.21	65.10	63.27

Table II.6 *Table showing the relative bias in MSYand f_{MSY}*

	0		25		50		75		100	
	A	B	A	B	A	B	A	B	A	B
Error in Catch = 0										
msy	0	-1.62	19.81	20.71	94.44	94.38	-17.75	39.94	9.96	50.77
fmsy	0	-2.65	20.70	7.92	25.19	-23.74	-28.84	-42.62	-7.07	-41.46
Error in Catch = 10										
msy	21.70	352.15	16.02	251.59	27.74	277.54	34.96	65.95	380.12	127.68
fmsy	10.59	-34.01	3.72	-5.58	14.68	-9.37	-22.16	-37.13	33.65	-38.03
Error in Catch = 20										
msy	37.14	288.20	1.59	471.19	-2.21	120.67	239.55	259.82	1.87	26.09
fmsy	-20.36	-45.32	-18.00	-32.23	-16.99	-46.15	-58.56	-57.74	-41.22	-53.14

Table II.6(contd) *Table showing the relative bias in MSY and f_{MSY}*

	0		25		50		75		100	
	A	B	A	B	A	B	A	B	A	B
Error in Catch =	***30***									
msy	174.57	395.72	62.53	567.06	272.23	62.08	638.77	1087.3	129.26	404.41
fmsy	6.96	-28.74	-40.40	-65.12	-46.41	-59.60	-52.15	-52.92	3.46	-44.83
Error in Catch =	***40***									
msy	4.04	114.31	136.12	313.64	3401.2	329.10	-5.28	98.58	431.14	136.79
fmsy	-51.66	-55.07	-25.87	-43.58	-54.69	-62.18	-57.72	-60.43	-43.44	-49.80

It can be seen from the Table II.1 that when both process and observation errors are zero, model **A** estimates with almost zero bias but not the model **B**. The reason for this could be attributed to the fact that the population simulated was based on the discrete form of the Schaefer model and not on the basis of the continuous form. However, the biases and the relative variation in the estimates of the parameters are not large enough and so it is assumed that further comparison would bring out differences in the models.

From the tables of the relative bias in the estimates of r, k, q, MSY and f_{MSY} the following observations could be made.

- The two models react differently in the presence of both process and observation errors.

- The coefficient of variation of the estimates of the parameters obtained from model **A** was lower than those obtained from model **B**.

- At higher levels of the process errors the model **B** tends to estimate q with relatively lesser bias than model **A**.

- Both the models overestimated r and q in most of the cases and in general the relative bias in these estimates obtained from model **B** were lower compared to that obtained from model **A**.

- The maximum sustainable yield tended to be overestimated from both the models and the models under estimated the optimal effort.

Thus from the point of view of estimating the basic parameters of the production model, namely, r, k and q, the continuous form (model **B**) of the Schaefer's model seems to be better choice than the discrete form. Although model **A** resulted in estimates with lesser coefficient of variation, because of the larger magnitudes of the bias in the estimates precludes the choice of the discrete form.

However, from the management point of view both models tended to over estimate MSY and under estimate f_{MSY}. In this, nevertheless, the discrete form was observed to outperform the continuous form because in general the biases in the estimates of MSY and f_{MSY} were lower for the discrete form.

Thus, we have conflicting options before us. Production models tend to estimate some quantities much more precisely than others. For most stocks, the marine biological reference points (MSY, f_{MSY}) are estimated relatively precisely (Prager. *op.cit*). The estimates of stock level and fishing mortality are usually estimated less precisely. This is due to the fact that q (the catchability coefficient) is imprecisely estimated. According Prager (*op.cit*) if a parameterization involving K and r is used in fitting, the estimates of these quantities are usually quite imprecise. However, because there are correlated the corresponding estimates of MSY and the optimum effort can none the less be quite precise. These observations seem to be in good agreement with the results obtained in the case of both the models used.

Ludwig (1980), pointed out that if random fluctuations are taken into consideration, the assessment of management strategies was more complicated. While examining the alternative harvesting strategies for three laws of population dynamics, namely, Beverton & Holt, the logistic model and the Pella-Tomlinson model ,also found out that the results of the harvesting strategies changes with the noise level in the population and also depended on the type of the model used.

It is well known in the exploited fish populations, the estimates of the stock size and the catch (or yield) are subject to errors which are caused both by fishery dependent and fishery independent factors. In this context, Prager (*op.cit*) pointed out that, because process errors were propagated forward in time, it would seem that time series fisheries models (e.g. production models), should include process errors, so that the system could be modeled as correctly possible.

The results of Ludwig and Walters(*op.cit.*) and Polacheck *et.al.*(*op.cit.*) are not directly comparable with the present findings as they have considered different manifestations of the surplus production models. It is worth noting that the conclusions on the effect of process errors and observation errors are ,in general, close agreement with the earlier similar studies. This study mainly attempted to evaluate the performance of the continuous and discrete forms of the Schaefer's model as given by Schnute(*op.cit.*) and recommends ,in general, the use of the continuous form for estimation of r,k and q. But from the management point of view the discrete form would be the better choice.

In conclusion it may be mentioned that the ability to choose between different formulations may be driven by the conflicting interests. In this context it may noted that the models based on simple equations without complete biological interpretaion such as the model proposed by Galto and Rinaldi (*op.cit*), the relative response model of Alagaraja (*op.cit*), and that of Roff(*op.cit.*) and Srinath (*op.cit*) may be quite useful in describing the fishery much more accurately and realistically for a given data set.

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CHAPTER III

CHAPTER III

MORTALITY RATES AND COHORT ANALYSIS

III. 1 Introduction

Information on mortality is critical to the study of population dynamics of exploited fish stocks. This forms an important input to the analytical models to derive the yield functions. There are two ways of expressing numerically the mortality in a population, the annual absolute rate of mortality and the instantaneous mortality rate. In fish population studies it is the latter which is very extensively used. The total instantaneous rate of mortality ,Z is composed of two components ,one due to fishing F and other due to natural causes ,M (Gulland, 1983). In the exploited fish populations the total mortality rate is usually estimated from the age composition of the catch. The various methods of estimating Z are given by Ricker (1975) and Sparre and Venema (1992) when the age composition of catch is available. However, in the tropics for many of the stocks age determination poses problems and in some cases practically impossible and as such the age based methods of estimating the mortality rates will not be feasible. Use of length measurements, i.e. the length frequency data in catch in combined with some assumption on the growth schedule of the exploited population is a well recognised approach for estimating the population parameters such as the instantaneous rates of mortality.

In this chapter some of the most commonly methods of estimating the instantaneous total mortality rate ,Z and the instantaneous natural mortality rate , M using the length composition of the catch for a given growth function are reviewed. An alternative estimate of Z is also proposed. The average length and the variance in length in a time (or age) interval are derived assuming an appropriate growth formula. Effect of finite exploited life span on the estimates of Z is investigated. Also, a simple empirical relationship is presented to estimate the natural mortality rate , M, applicable to tropical conditions. An alternative algorithm is developed for the length cohort analysis.

III. 2 Review

III.2 .1 Estimation of Z

If the number of deaths in a small interval of time is at all times proportional to the number of fish present at that time , the fraction which remain alive at time t is given by $N_t / N_o = \exp(-Z. t)$ where Z is the total instantaneous rate of mortality and Z = F + M, the sum of fishing and natural mortality rates.

If the age frequency data are available it is quite straightforward to estimate the mortality by using any of the classical estimators(Ricker, *op.cit.*).

When the regular age determination is impracticable , the length structure may be very useful in estimating the mortality rates, provided some measure of the growth rate is available (Beverton & Holt, 1956). The length frequency curve usually will have an ascending left limb and a descending right limb. This right limb is generated by the combined effect of total mortality and growth so it follows that if the growth rate is known the total mortality rate ,Z can be estimated.

Edser(1908) first noticed that if the logarithms of numbers in the length frequency data were plotted , the right hand limb was approximately a straight line. This is due to the fact the growth in length of fish over a limited range of age is approximately linear, so over this range, length can be taken as a direct index of age.

Assuming proportional increase of length with age Baranov(1918) developed the theory for estimating total mortality from the length frequency data. However, this is liabel to give distorted estimates because growth equations used were adequate fit over a limited range of age only.

Beverton & Holt (*op.cit.*) made use the theoretical representation of growth over full range of age to estimate Z. The growth equation developed by von Bertalanffy (1938) was used by them to represent Z as a function of mean length in the catch.

The growth equation is of the form

$$L_t = L_\infty [1 - \exp\{- K.(t - t_o)\}]$$

Where, L_t is the length of fish at age t, L_∞ is the asymptotic length , K is the Brody's growth coefficient and t_o is the age at which the length is zero.

Let the numbers at any age $t > t_c$ be given by

$N_t = R. \exp\{- Z (t - t_c)\}$ where t_c is the age corresponding to length at first capture.

Then number caught from $t = t_c$ to $t = \infty$ is

$$Y_n = F.\int_{t_c}^{\infty} N_t.dt$$

The total age of fish caught A $= F.\int_{t_c}^{\infty} t . N_t.dt$

Hence mean age of fish in the total catch from the year class t_c onwards is given by

$$t_{bar} = Y_n / A$$

Substituting for N_t and and integrating over the given range we get,

$$t_{bar} = t_c + 1 / Z.$$

For a population in a steady state this is also the average age of fish from t_c onwards in the annual catch.

An expression for mean length of fish in the catch can be derived in a similar way where,

$$L_{bar} = F.\int_{t_c}^{\infty} L_t N_t . dt \;/\; F.\int_{t_c}^{\infty} N_t . dt$$

Assuming the growth in length follows the von Bertalanffy formula(vBGF) , we have,

$$L_{bar} = L_\infty [1 - (Z/(Z+K))\exp\{-K(t_c - t_o)\}]$$

on rearranging the terms and assuming L_c is the length at first capture, the length of fish corresponding to the age at first capture, t_c , we have

$$Z = K . (L_\infty - L_{bar}) / (L_{bar} - L_c)$$

This is the expression derived by Beverton & Holt (*op.cit.*) to compute the total mortality rate, Z. Pauly (1983) suggested substituting L_c with L' where L' is the length from which the fish become fully vulnerable to the gear.

Ssentongo and Larkin (1973) have also proposed a simple method of estimate of Z from the length sample assuming vBGF in length. They derived an estimate of Z which is given by,

$$Z_s = K.\ (y_{bar} - y_c)^{-1}$$

where Z_s is estimate of Z, y_{bar} = mean of $(-\ln(1 - L_t / L_\infty))$

$$y_c = -\ln(1 - L_c / L_\infty)$$

Powell (1979) developed a more general expression for estimating Z/K. He gave a more accurate estimate of Z/K and L_∞ following the equation

$$(Z / K)_P = 2C^2/(1 - C^2) - \sigma_L^2(Z / K + 1) / [(L_\infty - L_c)^2(1 - C^2)]$$

where $C^2 = V_L ./(L_{bar} - L_c)^2$, V_L is the variance in length from L_c onwards and C^2 is coefficient of variation in length and σ_L^2 is the variance in the asymptotic lengths of fishes in the population. If it can be assumed that σ_L^2 is small compared to $(L_\infty - L_c)^2$, the second term in the above expression can be neglected so that $(Z/K)_P$ will now be equal to $2\ C^2\ /(1 - C^2)$. According to Powell (*op.cit.*) for large samples the Beverton & Holt estimator is unbiased.

Jones and van Zalinge (1981) ,assuming constant mortality with age and that the individual growth curves have the same L_∞ and K, derived an equation for determining the number greater than or equal to a given length in a single cohort. This formulation is then used to estimate Z from the length frequency data,which is given by,

$$\ln(\ \sum N\ ) = (\ Z\ /\ K)\ \ln(\ L_\infty - L) + \ln(\text{Constant})$$

where $\sum N$ is the cumulative catch in numbers from $L = L_C$ onwards(or L' onwards). This is commonly known as the Jones cumulative catch curve method.

Pauly(1983) proposed a length converted catch curve method which was of the form

$\ln(\ N_t/\Delta t) = a\ - Z.\ t^*$ where N_t is number caught in a length class, Δt is difference in age of the upper and lower limits in lengths of the length class, t^* is the average age corresponding to the upper and lower limits of length class. According to him, the term $N_t/\Delta t$ adjusted for what he termed as "pile up effect" which was caused by greater number of age classes falling in the larger length classes.

Srinath and Alagaraja(1981), assuming that the growth in length in the exploited phase to be linear, proposed an alternative estimate of Z which is to be solved by iteration from the following equation

$$Za\,(L_{bar} - L_o)/(L_M - L_o) = [1 - Z/(\exp(Za) - 1)]$$

where L_o(smallest fully represented) and L_M (largest) is the length in the catch , a is the difference in their age and L_{bar} is the average length in the catch from L_o onwards. They found that the estimate of Z derived from their method was in close agreement with those obtained from other methods.

Ehrhardt and Ault (1992) examined the bias of the Beverton & Holt - Z estimator when the length distributions were curtailed by gear selectivity within the range defined by L_c and L_λ (maximum length) and they also developed an alternative mortality model that may be more appropriate for the pattern of availability or selectivity obtained in tropical fisheries. They observed that under the conditions simulated by them, the Beverton&Holt estimator showed a large positive bias at low fishing mortality rates. High fishing mortality rates truncated length-frequency distributions and thus apparently forced less biased estimates.

III.2.2 Natural mortality rate

The total instantaneous rate of mortality is the sum of mortalities due to fishing and all factors other than fishing which is usually termed as natural mortality. Deaths due to predation, old age, disease etc. are all classified under natural mortality. This particular parameter is one of the most important inputs to almost all the structural models in fish stock assessment and also the most difficult to estimate. There is no direct method of estimating this parameter, especially in exploited fish populations. As fishing and natural mortality are assumed to concurrently affect the exploited stocks it is extremely difficult to make direct estimates of natural mortality. Since there is no direct method of estimating , M , proxy or auxiliary variables are used to derive estimates of M based on certain assumptions, some of those methods are reviewed hereunder.

In exploited fish populations the estimate of M can be obtained from the values of total mortality Z minus the fishing mortality or by plotting Z against effort and the intercept of such a plot gives an estimate of M (Ricker, *op.cit.*). This method of estimating M is not easy to follow in practice because more often than not, a good estimate of effective effort targeted at the exploited stock may not be available. Besides, in multispecies and multigear systems such as those prevalent in Indian waters, estimation of effective effort is quite impracticable. Thus , this practical difficulty of estimating M from this traditional and direct method has prompted many workers exploring comparative approaches which attempt to relate M to easy to estimate parameters or proxy variables.

Beverton & Holt (1959) and Holt (1960,1962) demonstrated the relationship between maximum age and the asymptotic size (T_{max} and L_∞) as well as between M and K (the parameter of vBGF). Tanaka (1960) as quoted by Saville (1977) has given a relationship between maximum age and M which can be used as a first approximation of M. Beverton (1963) emphasised that its statistical significance was doubtful because the accuracy of the data used was not known and the values obtained were in some cases certainly over or under estimates.

Rikhter and Efanov (1976) demonstrated a close association between M and age at sexual maturity and also age when 50% of the population was mature. They gave the following empirical relationship

$$M = 1.521 /(t_{m50})^{0.720} - 0.155$$

One of the most commonly used estimate of M is due to Pauly (1980), which he has developed compiling the information on 175 different stocks distributed in 84 species ranging from polar to tropical waters. He formulated an empirical relationship depicting M as a function of L_∞, K and T (mean annual temperature). The equation is of the form

$$\log(M) = -0.0066 - 0.279 \log(L_\infty) + 0.6543 \log(K) + 0.4634 \log(T)$$

Ursin (1984) questioned the statistical validity of the above equation and he also contended that the relation should be cautiously used because the accuracy of the input data were not known.

Alagaraja (1984) proposed an alternative method of estimating M by relating to the natural life span of fish which was defined as an age at which 99% of a cohort died if it had been exposed to natural mortality only and then derived the following relation

$M1\% = -\ln(0.01)/T_m$ where T_m is the natural life span of the fish.

More recently, Gunderson and Dygert (1988) estimated M as a function of reproductive effort and found that the commonly used reproductive effort index (Gonado-Somatic Weight Index) was superior to many of the life parameters as a better predictor of M. The equation was $M = 0.03 + 1.68$ WGSI , where WGSI is Gonado Somatic Weight Index.

Thus from the above review it is observed that not much of work has been done in comparing the various methods of estimating the mortality rates in respect of the biases, if any, and also the effect of sample size on the performance of the estimators. It is worthwhile also examining the performance of the estimators at different exploitation levels. In the following sections such an attempt is made. First the expressions for the average length and variance in length over a given time (or age) interval is derived as functions of the growth parameters. The general expressions for the above have also been given which can be suitably modified according to the assumption made on the exploitable life span, say finite or infinite. An alternative estimator of Z is also proposed and its performance is compared with that of the estimators due to Beverton & Hot and Ssentongo & Holt. Bootstrap methodology (Efron and Tibshirani, 1986) was employed to estimate the relative bias and also the coefficient of variation in the estimators , which would facilitate comparison between the proposed estimator and the other two already mentioned estimators.

III. 3 Average length and variance

Ssentongo and Larkin (*op.cit.*) have developed an estimate of Z by considering probability function of age p(t) from $t \geq t_c$ which is given by

$$p(t) = Z .\exp\{ -Z.(t - t_c)\}$$

From this we get the probability of age in the time interval (t_1 , t_2) as

$$p(t) = Z.\ h_o\ .\ \exp(-Z.t) \qquad t_1 \leq t \leq t_2$$

where $ho = [\exp(-Zt_1) - \exp(-Zt_2)]^{-1}$ where t_1 and t_2 are time variables.

Assuming the growth in length follows vBGF and assuming L_∞ and K are same for all fish (Jones and van Zalinge *op.cit.*) , the average length of fish in the interval (t_1, t_2) is

$$L_{bar} = E(L_t) = \int_{t_1}^{t_2} L_t.\ p(t)\, dt$$

substituting for L_t from the growth expression of vBGF and p(t) and integrating in the given range we get,

$$L_{bar} = L_\infty \left[1 - (Z/(Z+K)) \frac{e^{-(Z+K)t_1} - e^{-(Z+K)t_2}}{e^{-Zt_1} - e^{-Zt_2}} \right]$$

Let t_1 =p and t_2 = p + 1 the we get

$$L_{bar} = L_\infty [\ 1 - (Z/(Z+K))e^{-Kp} \{ (1 - e^{-(Z+K)})/(1 - e^{-Z}))\}] \text{ ...III.3.1}$$

It may be noted here that if $t_1 = t_c$ and $t_2 \rightarrow \infty$ then above equation reduces to

$$L_{bar} = L_\infty [\ 1 - (Z/(Z+K))e^{-Ktc}\ ]$$

$= L_\infty - (Z/(Z+K))(L_\infty - L_c)$ from which we get

$Z/K = [(L_\infty - L_{bar})/(L_{bar} - L_c)]$ which is nothing but the Beverton & Holt equation.

We know that $(1 - e^{-x})/x$ can be approximated to $e^{-0.5.x}$ if $x \leq 1.12$ the relative error from the exact value is about 5% and if $x \leq 1.6$ then it is about 10%.

Applying this approximation to the equation we see that

$$\mathbf{L_{bar} = L_\infty [\ 1 - e^{-K(p+0.5)}\ ]} \qquad \text{... III.3.2}$$

Thus, if the average length of fish is known at different unit intervals of time the above equation can be used to estimate $\mathbf{L_\infty}$ and **K** using the standard procedures of estimation available in fish population dynamics or by non linear regression approach. This is a significant result .

Now , the variance in length in $t_1 \leq t \leq t_2$ is

$$V(L) = E(L_t^2) - L_{bar}^2$$

$$E(L_t^2) = \int_{t_1}^{t_2} L_t^2 . p(t)\, dt$$

$$= L_\infty^2 \left[1 - (2.Z/(Z+K)) \left(\frac{e^{-(Z+K)t_1} - e^{-(Z+K)t_2}}{e^{-Zt_1} - e^{-Zt_2}} \right) \right.$$

$$\left. + (Z/(Z+2K) \left(\frac{e^{-(Z+2K)t_1} - e^{-(Z+2K)t_2}}{e^{-Zt_1} - e^{-Zt_2}} \right) \right]$$

Putting $t_1 = p$ and $t_2 = p+1$ we get

$$E(L_t^2) = L_\infty^2 \; [\, 1 - 2Z/(Z+k)\, e^{-Kp} (1 - e^{-(Z+K)})/(1 - e^{-Z})$$

$$+ Z/(Z+2K) e^{-2Kp} (1 - e^{-(Z+2K)})/(1 - e^{-Z}))\,]$$

From this we have $V(L) = E(L_t^2) - L_{bar}^2$, using this and after some simplification we get

$$V(L) = L_\infty^2 \, e^{-2Kp} \, [\, (Z/(Z+2K))(y_2/x_1) - (Z/(Z+K))^2.(y_1/x_1)^2]$$

where $y_2 = 1 - e^{-(Z+2K)}$ $y_1 = 1 - e^{-(Z+K)}$ $x_1 = 1 - e^{-Z}$

if $t_1 = t_c$ and $t_2 \to \infty$

$$V(L) = L_\infty^2 \, e^{-2Ktc} [\, (Z/(Z+2K)) - (Z/(Z+K))^2\,]$$

let $\theta = Z/K$

then $V(L) = (L_\infty - L_c)^2 [(\theta/(\theta + 2) - (\theta/(\theta+1))^2]$ III.3.3

Thus the equations III.3.1 and III.3.3 are general expressions for the mean and variance in length in a given age interval.

Now for $t_c \leq t \leq \infty$

$$V(L) = (L_\infty - L_c)^2 \; Z/(Z+2K) - (L_\infty - L_c)^2 (Z/(Z+K))^2$$

Substituting for $Z/K = (L_\infty - L_{bar})/(L_{bar} - L_c)$ we have,

$$V(L) = (L_\infty - L_c)^2 \; Z/(Z+2K) - (L_\infty - L_{bar})^2$$

let $\theta_1 = (L_\infty - L_c)$ and $\theta_2 = (L_\infty - L_\infty)$ and $V(L) = v$

so we have

$$v = \theta_1^2 (\theta/(\theta+2)) - \theta_2^2$$

from this we get $\theta = 2(v + \theta_2^2)/(\theta_1^2 - \theta_2^2 - v)$

since $\theta = Z/K$ we have,

$$\mathbf{Z_v = 2.K. (v + \theta_2^2)/(\theta_1^2 - \theta_2^2 - v)} \quad \textbf{... III.3.4}$$

from this the estimate of Z can be obtained . This is the proposed estimator of Z.

Obviously, the above estimate is a biased estimator , because of its complexity the analytical expressions of its bias and variance could not be found out. However, according to Efron and Tibshirani (*op.cit.*) bootstrap methodology can be employed for such complex functions to estimate the bias and variance.

III.4 Estimation of Z for finite exploitable life span

The estimates of Beverton&Holt , Ssentongo&Larkin and the one derived above assume steady state conditions and infinite exploitable life span. However, in the tropics where most species have high rates of growth and natural mortality and thus are short lived. Besides, tropical fisheries are characterised by multispecies and multigear systems operating with gears that have restrictive operational ranges and highly selective gears (Ehrhardt & Ault, *op.cit.*). This type of exploitation naturally results in a truncated length frequency data in catch between L_c and L_λ ($L_\lambda < L_\infty$) the maximum length in the catch.. The general expression for total mortality constrained by finite life span in the catch i.e. between t_c and t_λ, where t_λ is the maximum exploitable age of fish, with the corresponding lengths of L_c and L_λ is derived below.

III.4.1 General expression for Z

The probability density function of t for $t_c \leq t \leq t_\lambda$

$$p(t) = Z.e^{-Z(t - tc)} / (1 - e^{-Z(t\lambda - tc)})$$

let $a = t_\lambda - t_c$ so that

$$p(t) = Z.e^{-Z(t - tc)} / (1 - e^{-Za})$$

Assuming the growth in length follows vBGF and for given L_∞, K, L_c and L_λ we have

$$L_{bar} = E(L_t) = \int_{t_c}^{t_\lambda} L_t.p(t)\,dt$$

substituting the corresponding expressions for L_t and p(t) , integration over the given limits , after some simplifications gives,

$$L_{bar} = L_\infty - (L_\infty - L_c)\,(Z/(Z+K))[\,(1 - e^{-(Z+K)a})/(\,1 - e^{-Za})] \quad \text{... III.4.1.1}$$

from this we get,

$$(L_\infty - L_{bar})/\,(L_\infty - L_c) = Z\ (1 - e^{-(Z+K)a})\,[(Z+K)(1 - e^{-Za})]^{-1}$$

It is easily verified as $t_\lambda \rightarrow \infty$ the expression for L_{bar} reduces to the one derived by Beverton and Holt.

let $u = (L_\infty - L_{bar})(L_\infty - L_c)^{-1}$

and

$$x = (1 - e^{-(Z+K)a})(1 - e^{-Za})^{-1}$$

thus $u = x.(Z/(Z+K))$

from this we get ,

$$Z/K = u / (x - u)$$

when the t_λ tends to infinity the above expression reduces to

$Z/K = u / (1 - u)$ which is nothing but the Beverton&Holt expression.

Thus the general expression for Z for fininte exploitable life span is given by

$$\mathbf{Z_g = K.\ u / (x - u)} \quad \text{... III.4.1.2}$$

Variance in length $V_L = E(L_t^2) - L_{bar}^2$

$$E(L_t^2) = \int_{t_c}^{t_\lambda} L_t^2 p(t).dt$$

$$E(L_t^2) = L_\infty^2 \Big[1 - 2 (L_\infty - L_c) Z (1 - e^{-(Z+K)a} .[L_\infty \quad (Z+K)(1 - e^{-Za})]^{-1} + (L_\infty - L_c)^2 Z (1 - e^{-(Z+2K)a} .[L_\infty^2 \quad (Z+2K)(1 - e^{-Za})]^{-1} \Big]$$

$$= L_\infty^2 - 2L_\infty(L_\infty - L_c)\, Z\, x(Z + K)\text{-}1 + (L\infty - Lc)^2 Z\; x_1.(L_\infty^2 (Z + 2K))^{-1}$$

where x is already defined elsewhere and x_1 is given by

$$x_1 = (1 - e^{-(Z+2K)a).})(1 - e^{-Za})^{-1}$$

Substituting for L_{bar} from the equation we have

$$V_L = (L_\infty - L_c)^2 Z x_1 / (Z + 2K) - (L_\infty - L_{bar})^2 \quad \text{...} \quad \text{III.4.1.3}$$

substituting $\theta = Z/K$, $\theta_1 = (L_\infty - L_c)$, $\theta_2 = (L_\infty - L_{bar})$ and $V_L = v$

we have $\theta = 2(v + \theta_2^2)/(x_1\theta_1^2 - \theta_2^2 - v)$

from this we have

$$Z'_g = 2.\,K(v + \theta_2^2)/(x_1\theta_1^2 - \theta_2^2 - v) \quad \text{....} \quad \text{III.4.1.4}$$

it may be noted here that for infinite exploitable life span x_1 will tend to unity and thus the above expression reduces to Z_v

Thus we have in the case of finite exploitable life span, the following expressions for the total instantaneous rate of mortality Z as,

$$Z_g = K.\ u\ /\ (x - u) \text{ and} \qquad \text{III.4.1.5}$$

$$Z'_g = K.\ 2(v + \theta_2^{\ 2})/(x_1\theta_1^{\ 2} - \theta_2^{\ 2} - v) \qquad \text{III.4.1.6}$$

Thus both the equations do not generate explicit solutions for Z and the total mortality rate must be obtained through iteration only.

III.4.2 Effect of finite life span on the estimators

The bias in estimating the true value of Z in the general case of finite life span using the classical Beverton&Holt, Ssentongo&Larkin and the proposed estimator Z_v which were derived on the assumption of infinite exploitable age is evaluated in the following section. As the expressions for the bias from these estimators are difficult to derive in their exact forms, bootstrap method (Efron and Tibshirani *op.cit.*) was employed to estimate the respective biases in the estimators and the coefficient of variation in them. This can be done by generating samples from given population values. For this the following approach was adopted.

1) It is assumed that the lengths are normally distributed in a given age interval with a given mean and variance.

2) For given values of L_∞, K, L_C samples of different sizes were generated for varying fishing mortality rates using the general expressions for mean and variance in length (equations III.4.1.1 and III.4.1.3)

3) The following input parameters were used

L_∞ = 20 cm K = 1 (per year) L_C =8 cm M = 1(per year) and annual fishing mortalities were 0.5,1,2,3,4 and 5 each for exploitable life spans of 0.5, 1,2, 3 years and infinite life span and sample sizes of 25,50,100 and 200.

For each of the parametric combination, samples were generated and bootstrap replications of 1000 were made to estimate the bias and the coefficient of variation. The results are presented in the tables III.1 to III.5 and discussed hereunder.

Table III.1 Infinite exploitable life span

	B&H				BHV				ZSENTO			
	Sample size				**Sample size**				**Sample size**			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	16.45	13.38	11.27	11.35	22.56	18.75	19.02	19.83	13.1	10.6	6.93	4.84
1	14.24	11.55	7.62	5.54	18.81	14.84	13.17	9.96	20.2	18.79	15.98	18.14
2	15.58	10.05	6.94	4.84	18.36	15.42	11.63	10.76	21.55	17.83	17.65	17.4
3	14.71	10.74	8.26	5.84	18.82	15.16	12.12	11.71	20.63	17.55	17.32	16.19
4	15.01	10.62	7.84	5.74	19.13	15.71	13.84	11.66	20.78	17.14	14.84	14.7
5	14.59	11.24	7.52	5.06	19.14	15.34	13.35	12.1	20.62	18.34	15.66	13.38

Table III.2 Exploitable life span = 0.5 year

	B&H				BHV				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	102.4	102.5	102.5	102.5	101.7	102.4	102.5	102.5	102.5	102.5	102.5	102.5
1	90.49	93.42	98.31	95.21	75.8	78.37	82.26	77.77	100.4	101.4	102.39	102.4
2	47.3	46.67	46.65	45.27	32.71	30.74	30.25	28.78	68.06	67.03	67.55	65.38
3	28.82	25.17	26.21	25.08	21.28	15.22	13.21	10.6	46.37	43.59	44.22	42.66
4	19.6	16.01	11.33	11.13	17.19	12.9	7.77	6	32.93	31.11	28.86	26.54
5	16.63	14.57	10.6	7.82	16.67	14.19	9.61	7.12	27.29	25.62	24.39	22.43

Table III.3 Exploitable life span = 1.0 year

	B&H				BHV				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	29.17	47.6	48.34	48.89	36.09	33.77	34.03	35.29	66.16	64.87	65.91	65.94
1	26.76	27.47	23.34	23.72	19.29	18.25	11.57	10.12	44.45	43.51	41.43	41.2
2	16.43	12.88	9.96	10.34	16.1	12.13	9.52	6.5	27.21	24.41	23.84	25.91
3	15.63	10.89	8.79	5.65	18.34	13.79	11.37	11.62	23.13	20.25	20.67	16.29
4	14.24	9.7	6	5.79	18.28	13.87	13.5	12.71	20.26	17.75	14.71	15.68
5	15.2	10.37	6.33	5.6	18.5	13.05	11.88	12.43	21.26	18.18	16.12	15.36

Table III.4 Exploitable life span = 2.0 year

	B&H				BHV				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	14.44	10.26	6.57	6.09	16.79	13.79	9.85	8.63	18.73	14.82	14	14.37
1	15.36	10.83	28.35	5.56	17.41	14.12	11.57	11.94	23.7	19.69	18.48	17.07
2	14.83	11.51	9.17	5.44	18.54	14.73	12.17	11.34	21.08	20.14	18.5	16.43
3	13.65	10.99	8.12	5.68	17.51	14.87	10.63	12.28	18.87	18.22	17.88	15.54
4	15.49	10.52	7.82	6.05	19.24	14.94	13.17	9.45	21.06	17.55	16.16	18.62
5	15.2	12.44	7.94	5.62	18.69	16.47	13.51	12.19	20.72	16.96	16.07	15.77

Table III.5 Exploitable life span = 3.0 year

	B&H					BHV			ZSENTO			
	Sample size					Sample size			Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	15.05	16.69	8.79	9.3	20.53	17.68	15.9	17.68	13.26	10.2	7.68	4.06
1	15.09	10.99	7.56	5.25	17.86	14.37	13	11.78	22.47	18.92	16.15	15.08
2	15.09	11.07	7.44	5.59	18.69	14.74	13.5	12.89	20.87	18.23	15.27	16.65
3	16.33	10.52	8.93	5.39	18.23	13.31	14.06	11.58	22.44	17.48	16.74	15.56
4	15.31	11.15	8.67	5.69	18.69	14.97	13.9	12.38	20.99	18.01	16.08	15.4
5	17.43	9.77	8.27	5.47	20.21	15.09	12.5	12.56	21.83	17.45	17.24	14.92

III .4.2.1 Percent relative bias

Infinite exploitable life span

It is obvious from the tables the biases in all the estimators have decreased with the increase in the sample size. Except in the case of low fishing mortality rate of F=0.5 , the estimator due to Beverton & Holt had lesser bias than the other two estimators. Interestingly for a low fishing mortality (F=0.5) Ssentongo&Larkin estimator had the lowest bias. However, at higher fishing mortalities the proposed estimator fared better than that due to Ssentongo&Larkin.

Exploitable life span=0.5 year

In this case all the estimators fared poorly irrespective of the sample size. A notable feature here is that as the exploitation rate than the other two. It indicates that for short lived species with higher exploitation rates, the proposed estimator is likely to be reasonably good choice for estimating Z especially for larger sample sizes.

Exploitable life span=1.0 year

Irrespective of the fishing mortality rate and the sample size the Ssentongo&Larkin estimator fared rather badly as compared to other two estimators. Upto a fishing mortality rate of F=3.0 that is upto an exploitation rate (F/Z) of 0.75, the proposed estimator had lesser bias than the Beverton&Holt estimator. At very high exploitation rates however, the Beverton&Holt estimator had lesser bias. This suggests even at relatively high exploitation rates for a finite life span of 1 year , proposed estimator performed well.

Exploitable life span =2 years

As in the previous cases the magnitude of relative bias decreased with large sample size irrespective of the rate of fishing. Here also the proposed estimator had lesser bias than the rest for exploitation rates upto(F/Z 0.5). Again the Beverton&Holt estimator exhibited lesser biases at higher fishing rates.

Exploitable life span =3 years

At a very low fishing mortality rate , the relative bias was lowest for Ssentongo&Larkin estimator, which agrees with the result obtained in the case of infinite exploitable life span. At higher fishing rates however the Beverton&Holt estimator had the lesser bias which was again in conformity with the case of infinite exploitable life span.

It may be mentioned here that the results for Beverton&Holt are in close agreement with those obtained by Erhardt&Ault(*op.cit.*).

III.4.2.2. Coefficient of variation

The bootstrap coefficients of variation in the estimators are presented in tables III.6 to III.10.

Table III.6 Infinite exploitable life span

	B&H				B&H-V				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	17.07	13.25	9.03	5.5	20.08	16.83	10.24	6.14	14.43	10.03	8.47	4.84
1	13.23	14.39	9.1	6.33	15.88	17.71	10.66	7.84	10.45	12.35	8.32	5.59
2	16.78	15.34	8.71	6.83	20.62	18.61	10.85	8.39	12.39	11.44	3.15	5.88
3	16.37	11.48	10.81	6.12	20.3	13.24	12.93	7.42	14.58	10.5	8.78	5.38
4	19.51	12.43	8.68	6.41	23.11	16.9	10.37	7.48	16.88	8.38	9	5.98
5	13.81	10.51	9.46	6.5	15.89	13.27	11.59	8.23	11.9	7.8	8.01	5.4

Table III.7 Exploitable life span =0.5 year

	B&H				B&H-V				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	15.27	8.64	6.27	4.14	16.64	9.61	6.84	4.64	13.89	7.72	5.73	3.66
1	14.18	10.61	7.32	4.75	17.59	12.27	8.26	5.84	11.04	9.12	6.56	3.77
2	14.59	11.46	8.89	6.1	17.82	13.85	10.49	7.2	11.19	9.12	7.37	6.15
3	17.01	11.7	7.88	6.29	21.32	13.95	9.56	7.69	13.86	9.09	6.56	5.15
4	18.44	13.54	9.29	6.12	24.18	16.49	10.8	7.34	12.83	10.49	9.17	5.41
5	19.01	15.12	8.82	6.46	25.02	17.97	10.47	7.72	13.38	12.41	7.56	5.97

Table III.8 Exploitable life span =1.0 year

	B&H				B&H-V				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	18.05	11.46	6.64	4.89	21.33	13.73	7.85	5.57	14.6	9.29	5.6	4.6
1	17.2	14.43	8.62	5.8	21.07	16.86	10.23	6.83	22.52	13.95	6.93	4.89
2	16.96	12.88	9.07	5.95	23.01	15.41	10.88	7.29	11.66	10.46	7.26	6.09
3	17.89	14.02	8.18	6.37	22.37	15.66	10.02	7.93	14.49	14.94	6.81	5.34
4	20.49	13.39	9.15	6.3	24.83	15.74	10.93	7.97	19.06	11.91	7.82	5.46
5	20.98	10.34	10.6	5.41	24.92	13.28	12.71	6.51	16.04	7.8	8.37	5.23

Table III.9 Exploitable life span = 2.0 years

	B&H				B&H-V				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	21.32	12.39	7.49	6.08	22.72	13.88	9.05	7.06	21.33	11.55	6.1	5.47
1	20.04	12.77	9.16	5.04	24.31	16.41	11.7	5.59	19.63	10.46	6.61	6.16
2	18.04	13.32	9.5	6.58	20.35	15.93	11.77	7.75	20.48	11.83	7.49	6.22
3	17.08	13.46	8.62	6.81	19.72	15.83	10.26	8.02	13.28	11.11	7.16	6.68
4	18.07	14.06	9.22	6.76	21.95	18.16	10.96	8.19	14.87	9.74	8.87	5.81
5	21.25	11.98	9.25	6.65	25.21	15.08	11.57	8.1	16.93	9.61	6.99	5.32

Table III.10 Exploitable life span = 3.0 year

	B&H				B&H-V				ZSENTO			
	Sample size				Sample size				Sample size			
F	25	50	100	200	25	50	100	200	25	50	100	200
0.5	18.59	10.82	9.15	6.45	22.24	12.43	10.45	7.63	14.88	9.63	8.29	5.56
1	21.22	11.92	10.46	6.31	26.17	14.22	12.91	7.47	15.59	9.56	8.36	5.19
2	15.48	13.12	9.81	5.97	20.33	14.91	11.86	7.46	12.05	11.81	9.05	4.99
3	17.35	12.83	9.56	7.4	18.43	16.47	10.61	9.42	17.13	8.88	10.31	5.91
4	23	12.93	8.13	7.07	27.31	16.1	10.12	8.34	16.89	9.94	8.03	5.93
5	18.04	12.83	9.33	6.58	25.35	15.55	11.56	8.19	13.16	11.48	7.74	6.17

Significantly, a very different picture emerges from these results. Although, the Ssentongo&Larkin estimator had more pronounced relative bias than the other estimators, its coefficient of variation for different sample sizes and increasing fishing mortality rates was less than the remaining two estimators. If we consider a coefficient of variation of $\leq 20\%$ as indicator of stability of the estimator (which seems reasonable in highly dynamic fish populations) then all the three estimators seemed to be stable for sample sizes of more than 25. For larger sample sizes($\geq$ 100) the coefficient of variation in general was less than 15% which is quite satisfactory.

The population parameters of growth (L_∞ ,K) , natural mortality, and the length at first capture L_c are all typical of short lived tropical fish stocks and as such it is expected that the comparison between the estimators seems quite valid. Although the Beverton&Holt estimator tended to have lower bias at very high fishing mortality rates, the proposed estimator also performed very well for high exploitation rates. For larger samples, these estimates were quite stable from the point of view of their coefficient of variation in them. According to Ehrhardt and Ault (*op.cit.*) the Beverton&Holt estimator showed a large positive bias at low fishing mortality rates. High fishing mortality rates truncated length-frequency distributions and thus apparently forced less biased estimates.

III. 5 NATURAL MORTALITY RATE

Ursin (1984) and Alagaraja (1989) expressed doubts about the statistical validity of the Pauly's empirical equation to estimate M. Keeping in view of the fact in tropics the variations in sea temperatures are of lesser magnitude than prevalent in the temperate waters, the data given by Pauly (*op.cit.*) was re-analysed by taking into consideration only those groups which belonged to the temperature range of 26 - 28° C , which is the mean annual temperature range obtained in the tropical waters.

The following equations were fitted to the data,

$$y = b_o\, x_1^{b1}\, x_2^{b2} \quad \text{----- Equation 1}$$

and

$$y = c_o + c_1.x_1 + c_2.x_2 \quad \text{-------- Equation 2}$$

where $y = M$, $x_1 = L_\infty$ and $x_2 = K$; b_o, b_1, b_2, c_o, c_1 and c_2 are constants to be estimated.

As the temperature range was narrow and also due to the fact it was correlated with K(Ursin *op.cit*) it was not considered in the above equations. Following the classical regression analysis, the data were fitted to the above equations and the results are summarised below.

Equation 1:

Coefficient	Estimate	Standard error	Remarks
b_o	3.0122	0.4281*	Significant
b_1	-0.1190	0.1269	Not significant
b_2	0.7992	0.0998	Highly significant
R^2	72.73%		

(Standard error of b_o in log scale , the estimated $\log(b_o)$ being 1.1027 Significant indicates significant at 5% level and highly significant indicates significance at 1% level)*

Equation 2:

Coefficient	Estimate	Standard error	Remarks
c_0	0.6446	0.1737	Highly significant
c_1	-0.0029	0.002095	Not significant
c_2	1.4331	0.0939	Highly significant
R^2	84.97%		

From the above tables it is clear that in the chosen temperature range the contribution of L_∞ was not significant and K alone could be considered as a predictor of M. It is also notable that the linear form fitted the data better than the non-linear equation(Equation 1). In view of the above observations the following empirical relationship was found to be a better fit of the data, namely

$$\mathbf{M = \underset{(.1107)}{0.4615} + \underset{(.0897)}{1.4753}\,K \quad with\ R^2 = 84.4\%} \qquad \textbf{Equation. 3}$$

(The figures in the parenthesis indicate the standard errors of the estimates.)

An alternative form of the above relationship was also derived by forcing the line to pass through the origin, and the relationship now takes the form,

$$\mathbf{M = \underset{(0.081)}{1.68}\ K \quad with\ R^2 = 89.4\%} \qquad \textbf{Equation. 4}$$

(The figure in the parenthesis indicate the standard error of the estimate.)

Both the relationships are better fits to the data in the chosen temperature range than Pauly's equation whose R^2 was about 71% only. Thus, in the tropics above relationships could profitably used to estimate the natural mortality rate.

It is worth noting here that following the approach of Alagaraja (*op.cit*) if we assume that , under no exploitation, 99% of the stock die when then reach 95% of L_∞ then it is easy to very that $M/K \approx 1.54$. This can also be obtained from the concept of T_{max} which according to Pauly(op.cit) is approximately equal to 3/K. Thus if we assume that 99% of the stock (in the unexploited case) die when they reach T_{max}, we will obtain $M/K \approx 1.535$. The derivation is quite straightforward and is given below.

$$N_{Tmax} / N_o = \exp(-M.T_{max})$$

$0.01 = \exp(-M.3/K)$ from which it is easy to verify that $M = 1.535\ K$.

This equation and the equation. 4 result in constant M/K ratio irrespective of the magnitude of K which may be true in the case of more or less homogeneous groups or species sharing a common habitat. However , for all practical purposes the equation 3 can be used to estimate M.

However, since these relationships are also derived from the data set presented in Pauly(*op.cit*) , the observations made by Ursin(*op.cit*) are also applicable especially with reference to the precision of the estimates of M used taken from other studies and used in building the equation. Nonetheless, these equations serve as better approximations of M and statistically more valid than the one proposed by Pauly(*op.cit*). Besides it is not proper to estimate the mortality of the groups habitating a relatively narrow temperature range such as the one occurring in the tropics , from an equation which is built by taking into consideration highly heterogeneous temperature ranges, some of which never are obtained in the tropics.

III.6 Length cohort analysis

The length cohort analysis (Jones 1984) is a derived form of age based cohort analysis of Pope(1972). This approach is basically same as the length converted catch curve where the age frequency data is transformed to length frequency data via a growth function in length. The assumptions for the validity of length cohort analysis are almost the same as that of the age based analysis except that the growth function is the vBGF. The aim is to make use of the length structure of the catch to estimate the population structure under certain assumptions and for some known growth and natural mortality parameters. This would facilitate in estimating the stock size, recruitment, spawning stock, fishing mortality etc. which are essential for fish stock assessment.

Assuming the growth equation in length is vBGF, the basic equation in the length cohort analysis(following the notations of Sparre and Venema (*op.cit.*)) is given by

$$N(L_1) = \left[N(L+)*H(L_1,L_2) + C(L_1,L_2)]* H(L_1,L_2) \right] \quad .... \text{III.6.1}$$

where $N(L_1)$ = number of fish that attain length L_1

$N(L_2)$ = number of fish that attain length L_2

$C(L_1,L_2)$ = number of fish caught in the length group (L_1,L_2)

and $H(L_1,L_2) = ((L_\infty - L_1)/(L_\infty - L_2))^{(M/2K)}$

where L_∞ ,K are the parameters of vBGF and M is the instantaneous rate of natural mortality.

The calculations are started from the last length group in the length frequency data and use the length based catch equation

$$C(L_1,L_2) = N(L_1)(F/Z)(1 - \exp(-Z\Delta t))$$

where F is the fishing mortality rate in the length group (L_1,L_2)

$Z = F + M$ and Δt is time taken to grow from L_1 to L_2 (time interval)

In the last length class corresponding to the catch in numbers larger than L_1 (the lower limit of the last length group) Δt is taken as ∞ and the above equation reduces to

$$C(L_1, \infty) = N(L_1)F/Z$$

from which we get $N(L_1) = C(L_1,\infty)Z/F$

using this and the equation III.6.1 , the numbers in the sea are recursively computed. Once these are available , the computation of mortality rates, standing stock etc. become straightforward and needs no elaboration and the procedure is given in Sparre and Venema(*op.cit*).

Usually for estimating the numbers at sea in the terminal length group, a value for F/Z (terminal exploitation rate) is assumed. According Jones(*op.cit*) the choice of F/Z depends on the extent of exploitation of the stock under study. For moderate to heavily exploited stocks a choice of $F/Z \geq 0.50$ ensures convergence of mortality rates.

In practice however, the choice of F/Z poses some problems. In this section an algorithm is developed which carries out the length cohort analysis not from the terminal length group but from a chosen length group.

In the heavily exploited stocks and also in the short lived species, constrained by the selectivity of the gear, the catches of the length classes at the fully vulnerable length class or nearby it are likely to be more representative than those that are far away. The following algorithm is based on this consideration only.

ALGORITHM

For a given values of L_∞ , K and M

(1) Choose a starting length group from where the calculations are to begin

(2) Specify the range of F/Z along with increment in F/Z in this range

(3) Start from the smallest value in the above range , since M is given calculate Z

(4) Calculate the numbers in the sea in the chosen length class from

$Z\,C_L\ /F(1 - \exp(-Z\Delta t))$ where C_L is the numbers caught in the chosen length group and Δt is the time interval for the length group

(5) Back calculate the number in sea using the equation III.6.1

(6) Calculate numbers forward in length groups

(7) If numbers in sea are negative or zero stop the calculations if so goto step (8) else increment F/Z goto step (4).

(8) See F/Z values at the larger length groups , if there is more or less concordance stop the routine and print results if not do the routine in the neighbourhood of the F/Z obtained in (7)

(9) Check again the F/Z values at the larger length groups , if there is no further improvement possible stop the calculations and print the results.

The computer program written in **Basica** is given in the hereunder. After loading the program and giving the run command it will prompt for input file The input file should contain line by line the following particulars

L_∞ K, number of length classes, lower limit of the first length group, class width and catch in numbers one by one.

Program for alternative length cohort analysis

```
10 CLS
20 KEY OFF
30 'SAVE"LCOHO1"
40 DIM N(50),C(50),L(50),DL(50),X1(50),X2(50),F(50),Z(20)
50 DIM E(50),MNS(50)
60 '
70 INPUT "FILE NAME: ",F$
80 OPEN F$ FOR INPUT AS #1
90 WHILE NOT EOF(1)
100 INPUT #1,L8
110 INPUT #1,K
120 INPUT #1,NL
130 INPUT #1,LMIN
140 INPUT #1,WID
150 FOR I=1 TO NL
160 INPUT #1,C(I)
170 NEXT I
180 WEND
190 CLOSE #1
200 CLS
210 PRINT TAB(30);"INPUT DATA"
220 PRINT TAB(30);"=========="
230 PRINT :PRINT
240 PRINT TAB(10);"L8 = ";L8;TAB(30);"K= ";K
250 PRINT :PRINT
260 FOR I=1 TO NL
270 L(I)=LMIN+(I-1)*WID
280 NEXT I
290 FOR I=1 TO NL
300 L(NL+1)=L(NL)+WID
310 DL(I)=LOG((L8-L(I))/(L8-L(I+1)))
320 DL(I)=DL(I)/K
330 NEXT I
340 PRINT TAB(10);"SL. NO";TAB(20);"L-LEN";TAB(30);"CATCH"
350 PRINT
360 FOR I=1 TO NL
370 PRINT TAB(10);I;TAB(20);L(I);TAB(30);C(I)
380 NEXT I
390 PRINT :PRINT TAB(10);"STARTING LENGTH CLASS (SL.NO): ";:INPUT "",SL
400 IF SL<1 OR SL>NL THEN 200
410 INPUT "M/K = ",MK:M=MK*K
420 FOR I=1 TO NL
430 X1(I)=EXP(-.5*M*DL(I))
440 X2(I)=1/X1(I)
450 NEXT I
460 INPUT "MIN F/Z= ",EMIN
470 INPUT "MAX F/Z = ",EMAX
```

```
480 INPUT "INCR IN F/Z = ",EINC
490 FOR J=EMIN TO EMAX STEP EINC
500 MZ=1-J
510 Z=M/(1-J)
520 Z=Z*DL(SL)
530 U=J*(1-EXP(-Z))
540 N(SL)=C(SL)/U
550 GOSUB 930
560 FOR I=SL+1 TO NL
570 N(I)=X1(I-1)*(X1(I-1)*N(I-1)-C(I-1))
580 NEXT I
590 N(NL+1)=X1(NL)*(X1(NL)*N(NL)-C(NL))
600 IF N(NL+1)<=0 THEN GOSUB 980
610 CLS
620 IF ESTOP<>J THEN LOCATE 12,20:PRINT "--- PLEASE WAIT ---":GOTO 870
630 PRINT TAB(30);"RESULTS FOR F/Z = ";:PRINT USING "#.####";J:PRINT :PRINT
640 PRINT TAB(5);"M/K= ";:PRINT USING "#.##";MK;
650 PRINT TAB(25);"S.L. = ";:PRINT USING "####.##";L(SL)
660 PRINT
670 GOSUB 1050
680 FOR T=1 TO 65:PRINT TAB(4+T);"=";:NEXT:PRINT
690 PRINT TAB(5);" LENGTH";TAB(20);" CATCH";TAB(35);" POPLN";TAB(50);" F
";TAB(60);" F/Z"
700 FOR T=1 TO 65:PRINT TAB(4+T);"=";:NEXT :PRINT
710 PRINT
720 FOR I=1 TO NL
730 E(SL)=J
740 PRINT TAB(5);:PRINT USING "####.#";L(I);
750 PRINT TAB(20);:PRINT USING "######.###";C(I);
760 PRINT TAB(35);:PRINT USING "#######.###";N(I);
770 PRINT TAB(50);:PRINT USING "##.####";F(I);
780 PRINT TAB(60);:PRINT USING "#.####";E(I)
790 NEXT I
800 FOR T=1 TO 65:PRINT TAB(4+T);"=";:NEXT :PRINT
810 A$=INPUT$(1)
820 PRINT :PRINT "DO YOU WANT TO TRY NEAR F/Z = ";:PRINT USING "#.####";J
830 INPUT "IF YES TYPE ENTER ELSE N OR n  ",Y$
840 IF Y$="" THEN GOSUB 1150
850 IF Y$="N" OR Y$="n" THEN END
860 IF J=ESTOP THEN END
870 NEXT J
880 PRINT "NO PROBLEM UPTO F/Z = ";:PRINT USING "#.####";J-EINC:PRINT
890 PRINT "TRY AGAIN BEYOND F/Z= ";:PRINT USING "#.####";J-EINC
900 C$=INPUT$(1)
910 GOTO 200
920 END
930 '
940 FOR I=SL-1 TO 1 STEP -1
950 N(I)=(X2(I+1)*N(I+1)+C(I))*X2(I+1)
960 NEXT I
970 RETURN
980 '
990 PRINT "NUMBERS CAUGHT IS MORE THAN POPULATION ! "
```

```
1000 PRINT
1010 PRINT "FOR F/Z = ";:PRINT USING "#.####";J
1020 A$=INPUT$(1)
1030 CLS:GOSUB 1150
1040 RETURN
1050 '
1060 FOR I=1 TO NL-1
1070 E(I)=C(I)/(N(I)-N(I+1))
1080 E(NL)=C(NL)/N(NL)
1090 F(I)=M*E(I)/(1-E(I))
1100 Z(I)=F(I)+M
1110 NEXT I
1120 F(NL)=M*E(NL)/(1-E(NL))
1130 Z(NL)=F(NL)+M
1140 RETURN
1150 '
1160 CLS
1170 ESTOP=J-EINC
1180 DELX=ABS(E(NL)-ESTART)
1190 'PRINT DELX:D$=INPUT$(1)
1200 IF DELX<=.0001 THEN J=ESTOP:GOTO 630
1210 IF DELX>.0001 THEN 1220
1220 EMIN=J
1230 EMAX=J+EINC
1240 EINC=.0001
1250 ESTART=E(NL)
1260 GOTO 490
1270 RETURN
```

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CHAPTER IV

CHAPTER IV

TIME SERIES MODELLING OF MARINE FISH LANDINGS

IV.1 Introduction

The dynamics of exploited fish populations have traditionally been understood through inter-relationship of catch and effort;variation in catch in relation to oceanographic and environmental parameters or simply variations in catch over time. Models which take into account of the relationship between catch and effort have already been discussed elsewhere. These 'deterministic' models are based on 'a priori' assumptions about the nature of population growth, the relationship between fishing effort and the population size and form of relationship between yield and fishing effort. The major responsibility of fisheries managers is to determine the long term policies that will provide sustainable and near optimum return from the stocks. In contrast, the users of the resources presently want short term forecasts to make decisions regarding investment, fleet size, gear type etc. It is well known that the variations in the exploited stock size not only depend on the fishery dependent factors such as fleet size, type of gear and mesh used etc. but also depends on the fluctuations in the fishery independent variables such as the sea surface temperature, upwelling, windspeed, wind direction and other biophysical and ocean related parameters. An ideal model will be the one which is built around all the fishery dependent and fishery independent factors. Obviously such an ideal formulation of fisheries model is not a practical proposition because of its obvious complexity and exorbitant cost involved in the collection of data on all the relevant parameters..

Usually, the holistic dynamics of the stocks are explained with the help of catch-effort relationship,wherever such data are available. However, in most of the fisheries reliable estimates of fishing effort may not be available which is often the case with the multispecies and multigear system prevailing in the tropical waters. Analytical methods as given in Sparre and Venema (1992) could of course be applied for stock assessment whose data requirements are more rigorous. After all, the main purpose of these approaches is not only to describe the fishery but also to provide short term forecasts.

Time series analysis is an economical method for forecasting catches that could be widely applied as one of several methods in fishery forecasting. Its applicability in economics is well recognised and in fisheries it is slowly gaining importance. Some of the recent studies on application of time series analysis in fisheries and the methodology of auto regressive integrated moving average (ARIMA) by Box-Jenkins is reviewed hereunder.

In the approach to time series analysis proposed by Box-Jenkins (1976), which is now popular, both moving average terms and auto regressive terms are tested in a standardized procedure. Autoregressive terms may some times be interpreted in terms of such biological phenomena as reproductive time lags, where as the moving average terms that are based on differences between predicted and observed values of a series are not easily interpreted.

IV.2 Review

IV.2.1 Review of timeseries modelling in marine fisheries

Chakraborty(1973) attempted polynomial regression in timeseries of marine fish landings in India. Shastri (1978) also carriedout a similar trend analysis.

Dyer and Gillooly (1979) studied the variations over time of the total annual production of pelagic fish for South Africa and the United Kingdom quantitatively using the exponential smoothing technique. The exercise was repeated on annual mackerel landings for the same two countries. It was suggested in some cases the production figure for the current year can be used to simulate the following years value. The greater variations in the South Africa's annual production resulted in poorer predictability.

Van Winkle *et.al.* (1979) used autocorrelation and spectral analysis techniques to examine the periodicity in the dominant year classes of Atlantic coast striped bass (*Morone saxatilis*) commercial fisheries data. Their analysis did not support the hypothesis of a pronounced or a simple cycle of 6 year or any other time interval in the appearance of the dominant year classes. They concluded that impact assessment and monitoring programmes should not be predicted on the expectation of such cycles.

Saila *et.al.* (1980) compared some time-series models for analysis of fisheries data. The three procedures, monthly averages, harmonic regression analysis and autoregressive integrated moving average models were briefly described and evaluated using the variance of the residuals of the original observations and forecasts compared with actual data not used in developing the models. An ARIMA(AutoRegressive Integrated Moving Average) model was found to be the most suitable in terms of producing forecasts upto 12 months ahead.

The predictive power of stock production models and some time series methods were considered for five marine fish stocks by Stocker and Hillborn (1981). The distinction between model fitting and forecasting future short term catch was discussed as was the difference between techniques to forecast short term yield and techniques to calculate long term management practices. Fox's procedure for fitting Pella and Tomlinson stock production model; Schnute's method for fitting Schaeffer's model and Gulland's method were all considered. They found that all methods except that of Gulland worked well for some stocks and the relative performance of the methods depended upon the exploitation history of the stock. In several instances one of the best forecast of the next year catch per unit effort(CPUE) was the previous year's CPUE emphasizing the fact that a good forecasting technique may have not ability in determining management policies.

In India the first ever attempt on modelling marine fish production using the Box-Jenkins approach was by Indian Institute of Management

(Anon 1984). In this study, The quarterly marine fish landings during 1960 to 1978 in each of the maritime states of India were considered for building up a multiplicative seasonal autoregressive models. The models were then used to forecast the fishery from 1979 to 1985. The forecasted values were found to be more or less in good agreement with the observed values.

Jensen (1985) analysed the catch and catch per unit effort data for Atlantic menhaden and the gulf menhaden of the Gulf of Mexico with the help of autocorrelation to test for time lags and to develop forecasting equations. The results for two species and for catch and CPUE data were considerably different. A six year time lag was found for both, the autocorrelation being positive in the Atlantic menhaden and negative in the Gulf of Mexico. According to him environmental factors such as change in the sea temperature could have caused the observed delayed density dependence but the time lags also could have arisen from a reproductive delay. The autocorrelation structure of the catch and CPUE data were applied to develop autoregressive models for year ahead forecasts whose predictive performance was found to be high.

Noakes (1985) demonstrated the efficiency of intervention analysis in fisheries science using the data from the Canadian Dungeness crab fishery. The autocorrelation function structure was considered for evaluating the change in the system response. He opined that the selection of the most appropriate model from a set of models passing diagnostic checks could be made on the basis of an objective criterion.

Srinath and Datta (1985) applied the ARIMA modeling to the Marine Products Export in India. This was perhaps the only attempt in India to model the marine product exports using the Box-Jenkins approach. They demonstrated the feasibility of ARIMA technique in forecasting and found that the forecasts were found to be closer to the actual values.

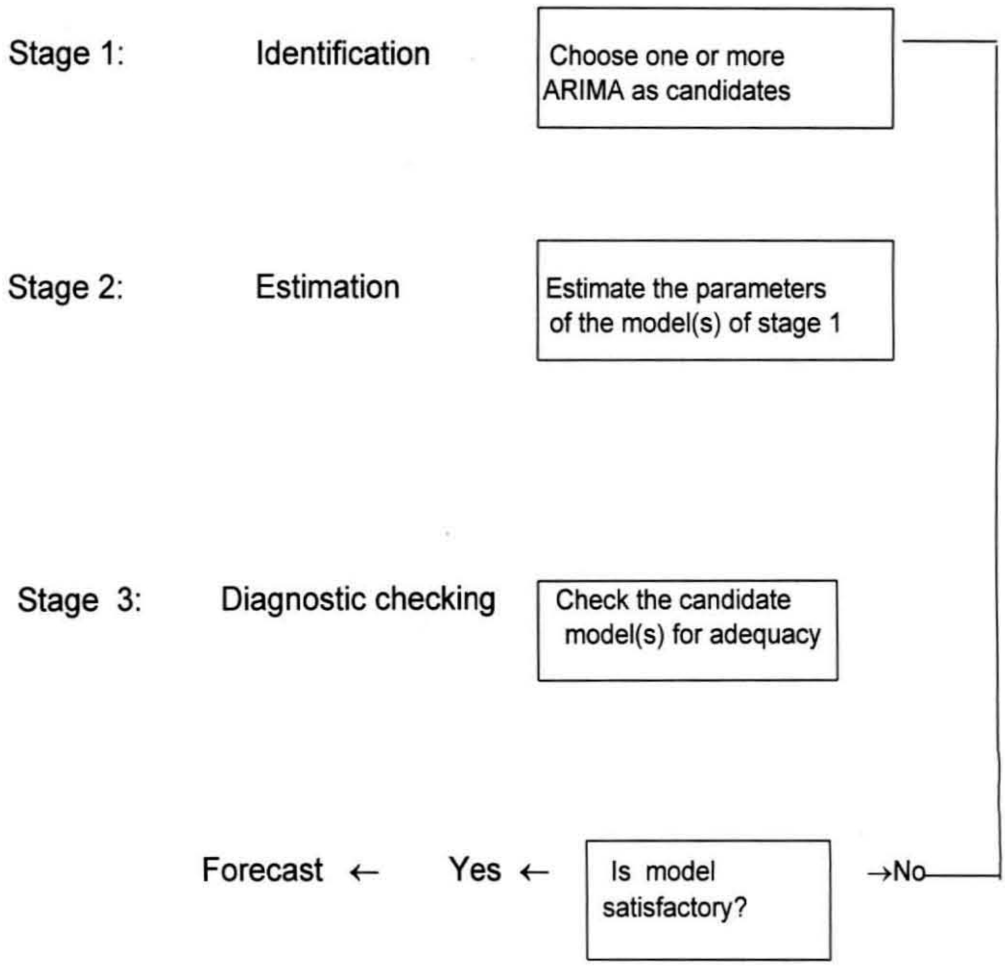
Rose *et.al* (1986) proposed a time series analysis method based on the use of categorized variables and ordinary least squares method. They contended that it had several advantages over the Box-Jenkins models and time series regression with continuous variables. Aspects of model building, significance testing and interpretation of the results were discussed and illustrated with a fisheries example involving an measure of white perch (*Morone americana*) stock size in the Delaware River/Bay from 1928 to 1974. Variation in white perch dynamics was analysed using the following explanatory variables: lagged values of stock;hydrographic variables(fresh water flow and water temperature) and pollution related variables and dissolved oxygen.

Fogarty(1988) used Box-Jenkins transfer function models to analyse the relationship between water temperature and Maine lobster catch and catch per unit effort(CPUE). He first modeled catch and CPUE with univariate ARIMA to provide a basis for comparison with transfer function models. An immediate temperature effect (lag 0-1 year) was demonstrated.

Stergiou(1989) analysed 17 year record of monthly catch of pilchard from Greek waters using the ARIMA techniques. He proposed two models suitable to describe the dynamics of the fishery for forecasting catches upto 12 months ahead. He stated that ARIMA procedures were capable of describing and forecasting the complex dynamics of Greek pilchard fishery. A seasonal autoregressive model of the Anchovy fishery in the Eastern Mediterranean was also presented by him (Stergiou, 1990). He found that the seasonal autoregressive terms of the model seemed to be consistent with the biological/oceanographic observations.

IV.2.2 A brief outline of ARIMA

Univariate autoregressive integrated moving average (ARIMA) models of Box-Jenkins especially are suited to short term forecasting because most of these models place emphasis on the recent past rather than the distant past. They make use of the interrelationship of observations in a series to describe the inherent process and give a neat mathematical representation of the relationship between the observations and the corresponding errors which facilitate prediction of the process. The models can be built around discrete or continuous data. The theory of ARIMA has seen well explained in many of the standard books(Box and Jenkins ,1976, Montgomery and Johnson ,1976 and Pankratz ,1983) and does not need any elaboration. However for completeness sake, only a schematic representation of the approach as given in Pankratz(*op.cit.*) is presented hereunder.



At the identification stage two graphical devices to measure the correlation between observations within a single data series are used namely, *autocorrelation function* (**acf**) and *partial autocorrelation function* (**pacf**). Depending upon the trend observed in the estimated acf and pacf, model(s) (as described by Box and Jenkins *op. cit.*) are tentatively chosen to describe the data. At the estimation stage, using certain statistical principles(Pankratz *op.cit*), estimates of the coefficients of the tentatively identified model(s) are made. Box and Jenkins(*op.cit*) suggest some diagnostic checks to help determine if the estimated model is statistically adequate such as the Box-Ljung Q- statistics based on the acf of the residuals. A model that fails these checks is rejected and the cycle is repeated until a good model is found. According to Pankratz(*op.cit*) it is wise to examine the estimated acf of the first differences even if differencing doesn't seem necessary to induce a stationary mean because the periodic pattern is often clearer in the acf of the first differences than in the acf of the original series.

ARIMA models may be characterized by ARIMA (p, d, q) where p is the autoregressive order, d is the number of times the series need to be differenced and q is the order of moving average.

The general model is of the form

$$\phi(B)\, \nabla^d\, \tilde{Z}_t \;=\; \theta(B)\, a_t$$

where $\tilde{Z}_t$ is the deviation of the series Z_t from its mean μ.

$$\nabla^d = (1 - B)^d$$

(1 - B) is the differencing operator and d is the order of the differencing.

$$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \ldots\ldots\ldots \phi_p B^p)$$

$$\theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \ldots\ldots\ldots \theta_q B^q)$$

where ϕ 's and θ's are the autoregressive and moving average coefficients respectively and a_t is the random shock..

According to Pankratz (*op.cit.*), the univariate Box-Jenkins ARIMA models have three advantages. First, the concepts are derived from an ideal foundation of classical theory of probability and mathematical statistics. Second, ARIMA are a family of models not just a single model. Box and Jenkins have developed a strategy that guides the analyst in observing one or more appropriate models out of the larger family of models. Third, it can be shown that an appropriate ARIMA model produces optimal forecast.

However, the construction of proper ARIMA models may require more experience and computer time than some historically popular univariate methods.

IV. 3 Database

The time series of data pertaining the marine fish landings on all India basis and for some important states are considered for this study. These data are obtained from the various publications and published reports of Central Marine Fisheries Research Institute(CMFRI *Bulletin No.* 13,*Marine Fisheries Information Service T&E Ser. Nos: 9,22,35,41,52,67,91 & 136* and Annual reports upto 1995). The landings data from 1961 to 1995 formed the data base.

The **trends** option in **SPSS/PC+** package has been used for ARIMA modelling. For selecting the appropriate model AIC (Akaike Information Criterion), SBC (Schwartz Bayesian Criterion), MAE (Mean Absolute Error) and RMS (Root Mean Square) along with the acf of the residuals and the Box-Jung Q- Statistics (Pankratz *op.cit*) were considered.

IV.4 Results

IV.4.1 All India

IV.4.1.1 Total landings

The estimated total marine fish landings in India during 1961 to 1995 ranged from a minimum of about 6.44 lakh tonnes in 1962 to about 23.58 lakh tonnes in 1994. Recently, there are indications of stagnation in the total landings. The trend of landings is depicted in Figure IV.1 .

The acf and the pacf of the total landings are given in figures(IV.2 and IV.3) . From the trend in the landings and those of the acf it is obvious that the series is nonstationary. The acf and pacf of the first difference of the series (figures IV.4 and IV.5) indicated that the series of the first difference could be stationary. From the pattern of the acf and pacf (Pankratz *op. cit.*) and ARIMA (1,1,0) was tentatively identified. The acf of the residuals (figure IV.6) conformed to that of the white noise process and the Box-Ljung Q - statistics at the autocorrelations were not significant. Thus for the all India total landings an ARIMA(1,1,0) with an auto regressive coefficient of -0.3466 and a constant term of 0.4827 would adequately fit the data and the fitted curve is given in figure (IV.1).

IV.4.1.2 Oilsardine

The Indian oil sardine (*Sardinella longiceps*) is one of the most commercially important pelagic resource. Its landings are characterized by wide year to year variations. It is used to be single most dominant component of marine fish landings in the country. However, of late its contribution has been decreasing. On all India basis the estimated landings fluctuated between 0.57 lakh tonnes in 1995 to about 3.01 lakh tonnes in 1968. Its variation along the Kerala coast has been very wide, ranging from about 0.02 lakh tonnes in 1994 to about 2.47 lakh tonnes in 1968. In Kerala its landings gradually decreased from 1.85 lakh tonnes in 1989 to 0.13 lakh tonnes in 1995 touching an all time low figure of 0.02 lakh tonnes during 1994. Similar trend prevailed along the Karnataka coast. However, in the east coast especially along the Tamilnadu coast there is entirely different trend. The landings upto eighties used to be very marginal but started showing an increasing trend 1981 onward. With a meagre 195 tonnes during 1981 it has shot upto about 36,000 tonnes in

1994. Similar increasing trend was observed along Andhra coast although quantitatively much less compared to Tamilnadu.

The causes of such wide variations in the landings have been investigated by many workers by attempting to study the effect of fishery dependent and fishery independent factors. However, no definite conclusions were arrived on possible causes in such variations except to point out that it might be due to both fishery dependent and fishery independent factors(Madhu Pratap *et. al. op. cit.*). Thus, prediction of oilsardine landings has always posed a problem using the conventional population dynamic models. However, here an attempt has been made to analyse the process with the help of ARIMA modelling and if possible develop a prediction equation. Later in the chapter an alternative approach has been attempted to fit an empirical model to the landings along the coast of Kerala with an explanation for possible causes in periodic variations in the landings.

The trend in the all India oil sardine landings is depicted in the Figure IV.7. The acf and pacf plots are given in Figures IV.8 and IV.9. Both acf and pacf cut off after lag 1 with acf showing spikes at lags 4 & 5 which were almost significant(As per the warning levels indicated by Pankratz *op.cit.*). Tentatively AR(1) process has been identified as the most probable model to describe the trend. None of the acf and pacf of the differenced series (Figs IV.10 and IV.11) is significant. However, according to Pankratz (*op.cit*), if the series has a cyclic or periodic behaviour, the correlation at periodic lags which are more than 1.25 times the standard error may have to be taken into consideration. For the differenced series it was observed that the correlation at lag 5 seems to satisfy this criterion. The trend of seasonal correlation(Fig IV.12) suggested a moving average process. Thus multiplicative seasonal model with a seasonal lag of 5 was tentatively identified to fit the process which was of the type ARIMA (1, 0, 0) $(0, 0, 1)_5$ with seasonal lag of 5. The following table shows the values of the criteria used for model selection.

MODEL	AIC	SBC	MAE	RMS
ARIMA(1,0,0)	385.98	389.08	43.031	58.072
ARIMA(1,0,0)$(0,0,1)_5$	383.54	387.21	40.842	56.328

Thus the table clearly indicated that the multiplicative seasonal model was an adequate fit and it was further confirmed by the acf of the residuals(Fig IV.13). The fitted curve is given in Fig. IV.7.

IV.4.1.3 Bombayduck

It is also a single species (*Harpodon nehereus*) pelagic resource and forms an important fishery along the northwest coast of India comprising the states of Maharashtra and Gujarat. It is also available in the northeast region along the West Bengal coast but in considerably lesser quantities than in the northwest. Although the landings of Bombayduck have also shown fluctuations over the years, its year to year variations are of lesser degree as compared to that of the oilsardine. During the period under study it touched a low of about 52000 tonnes during 1972 to a peak of about 138,000 tonnes during 1981. This peak was also attained during 1991, when the landings were about 136,000 tonnes.

Comparing the trend of landings in the state of Maharashtra and Gujarat, it was observed that in Maharashtra the landings were declining whereas no such trend was observed in Gujarat.. Assuming that the resource along these coast as of unit stock the all India trend in the landings from 1991 had been of decreasing one although no clear picture emerged from the overall trend pattern for 1961 to 1995(Fig IV.14).

The acf and pacf plots of the landings (Fig IV.15 and IV.16) suggest an AR(1) process. The acf and pacf of the first difference(Fig IV.17 and IV.18) indicated none of the correlation were significant also meaning that the process may be a random walk process of AR(0, 1, 0). The values of the criteria for the alternative models are given below.

MODEL	AIC	SBC	MAE	RMS
ARIMA(1,0,0)	307.53	310.64	15.029	18.934
ARIMA(0,1,0)	305.82	307.35	16.612	21.408

The AIC and SBC seemed to select the random walk model, although the MAE,RMS along with the acf of residuals suggested AR(1) process to be most likely model to fit the data. However from the trend of landings AR(0,1,0) was chosen as a likely model(Fig IV.14).

IV.4.1.3 Mackerel

The Indian mackerel (*Rastrilleger kanagurta*) is also a single species fishery and the resources are most abundant along the southwest coast in the states of Kerala, Karnataka and Goa. Of late it is also occurring in relatively larger quantities off Tamilnadu and Andhra coast. Like the other pelagic resources such as the oilsardine and bombayduck, it has also shown wide variations in the landings. On all Indian basis it has varied from a low of about 21 thousand tonnes in 1968 to about peak landings of about 280 thousand tonnes in 1989 again touching a high of about 249 thousand tonnes in 1993(Fig IV.19).

The fishery and population dynamics of this species has been studied by several workers. It formed along with oil sardine, an important component of the pelagic resources of the southwest coast of India. It also exhibited wide fluctuations from year to year although there was a general increasing trend from 1981 onwards. Kerala and Karnataka are the major contributors to the all India landings of this resource.

The acf and pacf of the mackerel landings (Fig IV.21 and IV.22) indicated an AR(1) process. However, the acf and pacf of the differenced series(Figs IV.23 and IV.24) indicated spikes at lags 2 and 4 which fell above the warning levels as suggested by Pankratz(*op.cit*). The reason for considering the diffrenced series was to explore possible periodicity in the original series. From the pattern of acf and pacf of the differnced series and acf of seasonal difference(Fig IV.25) , an $ARIMA(1,0,0)(1,1,0)_4$ was identified and tentatively selected. Thus we have two possible models to describe the landings. The criteria values for these models are given in the following table.

MODEL	AIC	SBC	MAE	RMS
AR(1,0,0)	377.528	380.64	37.172	51.733
ARIMA(1,0,0)(1,1,0)$_4$	335.68	339.98	33.714	50.851

Thus from the acf of the residuals(Fig IV.26) of the seasonal model and from the above table , the multiplicative seasonal model was found to fit the data better and hence selected to fit the data and the fitted curve is given in Fig IV.20. The Fit for AR(1) process is given in IV.19.

IV.4.1.4 Penaeid prawns

The penaeid prawns are by far the commercially most important resource exploited from the Indian waters because of their export potential. They form the bulk of the foreign exchange earnings among the marine products. It constitutes more than 80% of the value realised in the marine product export. The fishing effort in Indian marine fisheries is primarily directed towards exploiting this single resources. The resources of penaeid prawns are multispecies in nature occurring all along the Indian coast, predominantly, the west coast of India. Kerala, Maharashtra, Gujarat and Tamilnadu are the major contributors to the all India landings. Although there is qualitative and quantitative difference between the states, in respect of the species exploited, for this study , analysis was carried out on all India basis.

The trend in the landings of penaeid prawns is given in Fig IV.27 The acf and pacf (Fig. IV.28 and IV.29) indicates that the series is nonstationary. The acf and pacf of the first difference is given in Figs IV.30 and IV.31. and the plots suggested moving average process of the first difference (1, 1) namely ARIMA (0, 1, 1) . The acf of residuals(Fig IV.32) of this process resembled the white noise indicating the adequacy of the model to fit the data. The coefficient of moving average process was 0.6527 with a constant term of 4.7011. The fitted curve is given in Figure IV.27.

IV.4.2 Kerala

IV.4.2.1 Total

Kerala has been one of the leading states in marine fish production. Upto early nineties it was the largest contributor to the marine fish landings in India. Of late, Gujarat has surpassed Kerala to become the leading producer. The annual total landings ranged from 1.92 lakh tonnes in 1962 to 6.63 lakh tonnes in 1990 and thereafter the landings have been decreasing.

The trend in the annual landings is depicted in Fig. IV.33. The trend of the landings indicates that the series is nonstationary and it is also reflected in the pattern of the acf and pacf (Fig IV.34 and IV.35) . The acf and pacf of the first difference (Figs IV.36 and IV.37) indicated that the differenced series was stationary. None of the auto correlations in the differenced series were significant indicating perhaps, a random walk model AR(0,1,0) would be adequate to describe the total landings in Kerala. The performance of this model was compared with that of AR(1) process which the original series seemed to indicate , eventhough the series was not stationary. The values of the criteria for selection of the models are given in the following table.

MODEL	AIC	SBC	MAE	RMS
AR(1,0,0)	402.19	405.30	55.378	74.598
AR(0,1,0)	390..88	392.41	54.591	74.186

Since in the random walk the residuals are nothing but the first differences, the adequacy of the ARIMA(0,1,0) could be tested by the significance of the acf of the differenced series itself. In this case none of the correlations were significant so also the Box-Ljung Q- statistics. This along with the results of the above table indicated that AR(0,1,0) process would fit the data (Fig IV.33) better.

IV.4.2.2 Oilsardine

This is one of the most important pelagic resource exploited along the Kerala coast and the fishery is supported by a single species namely, *Sardinella longiceps*. The landings of oilsardine exhibited very wide yearly variations ranging from a peak of 247 thousand tonnes in 1968 to 1.6 thousand tonnes in 1994(Fig IV.38).

The acf and pacf of the series are plotted in Figs IV.39 and IV.40. The trend in the landings suggested an AR(1) process. The landings seemed to indicate some periodicity and so as suggested by Pankratz(*op.cit.*) the acf of first differences were investigated which showed spike at lags of 4 periods although the autocorrelations were all within the two standard error limit. The values at the spikes were above the warning level.The trend of acf and pacf of first difference (Fig IV.41 and IV.42) indicated a multiplicative seasonal model(acf of seasonal difference Fig IV.43) of the type ARIMA(1,0,0)$(1,0,0)_4$ might be adequate. Also it may be noted by considering only the acf based on the two standard error limit then we might as well consider ARIMA(0,1,0) process also. The values of the criteria for selection of the model are given below.

MODEL	AIC	SBC	MAE	RMS
ARIMA(0,1,0)	366.54	368.07	36.57	52.28
ARIMA(1,0,0)	374.06	377.17	39.01	49.12
ARIMA(1,0,0)$(1,0,0)_4$	366.74	368.41	36.16	48.47

From the above table it is seen both the random walk model and the seasonal model seemed to be adequate enough, although from the point of view of RMS (better predictive ability) , the seasonal model seemed to be better choice. The acf of the residuals (Fig IV.44) resembled that of a white noise process. The fitted curve is given in Fig IV.38 .

IV.4.2.3 Mackerel

The mackerel landings like the other important pelagic resource of Kerala namely oilsardine is characterised by year to year fluctuations. The landings varied from a low of 3.6 thousand tonnes during 1968 to 112 thousand tonnes in 1994. The late seventies and upto mid eighties witnessed poorer landings as compared that of the oilsardine. Of late there was a sudden spurt in the landings(Fig IV.45). From the trend in the landings and also that of acf and pacf (Fig IV.46 and IV.47) it was observed that the series was non stationary and perhaps needed differencing. The acf and pacf of the first difference series (IV.48 and IV.49) exhibited non-significant auto correlations except a spike at lag 3 which was above the warning level of 1.6 or 1.25 as the case may be (Pankratz *op cit*). The acf of seasonal difference of 3(Fig IV.50) showed a clear picture and confirmed a significant seasonal lag at 3. From this tentatively a multiplicative seasonal model of ARIMA (1,0,0) $(0,1,1)_3$ was identified. This model is compared with other probable models indicated in the following table.

Model	AIC	SBC	MAE	RMS
ARIMA (1,0,0)	317.93	321.04	15.851	21.869
ARIMA (0,1,0)	312.57	314.09	17.412	23.639
ARIMA $(1,0,0)(0,1,1)_3$	300.56	304.96	14.968	20.516

Thus the comparison showed the seasonal multiplicative model was adequate which was further confirmed by the acf of the residuals (Fig. IV.51) and the Box-Ljung statistics. The fitted curve is given in Fig IV.45. The auto regressive coefficient was 0.5943 and the seasonal moving average coefficient was 0.8167 with a constant term of 4.1969.

IV.4.2.4 Penaeid prawns

Kerala was the leading producer of this very important marine fishery resource. After reaching a peak of about 85 thousand tonnes in 1973 (Fig IV.52) the catches started dwindling upto mid eighties. Afterwards there seemed to a minor revival in the landings. The landings seemed to fluctuate around 35 to 40 thousand tonnes per year. The trend in the acf and pacf (Figs IV .53 and IV .54) clearly showed that it could be an AR(2) process. The acf of the residuals(Fig IV.55) was of white noise process and Box-Ljung -Q statistics was not significant. Thus AR (2,0,0) process was fitted to the data and with auto regressive coefficient of 0.301 and 0.318 respectively with a constant term of 40.708. The fitted curve is given in Fig IV.52.

IV.4.3 Tamil Nadu

IV.4.3.1 Total

Tamil Nadu ranks first among the maritime states of the east coast of India in respect of marine fish production. The landings ranged from a low of 1.06 lakh tonnes during 1965 to 4.22 lakh tonnes during 1995 (Fig IV.56.). In general, there has been steady increasing trend, with some year to year variations.

The acf and pacf of the total landings is given Figures IV.57 and IV.58. The trend in the acf suggests that the series is non-stationery and needs suitable transformation or differencing to make it stationary. The acf and pacf of the differenced series suggests (Figs IV.59 and IV.60) an auto regressive process of type ARIMA(2,1,0). The acf of the residuals (Fig IV.61) resembled that of a white noise process and the Box-Ljung statistics was not-significant. The fitted ARIMA(2,1,0) process is depicted in Figure IV.56 . The autoregressive coefficients were -0.2688 and -0.5689 respectively.

IV.4.3.2 Silverbellies

The multispecies stock of silverbellies is one of the most abundant marine resource along the Tamil Nadu coast and in the all India level Tamil Nadu ranks first in the landings of this group. The landings fluctuated between 6.42 thousand tonnes in 1961 and 48.93 thousand tonnes in 1995 with a peak landings of 62.12 thousand tonnes in 1983(Fig IV.62).

The acf and pacf of the series is given in Figures IV.63 and IV.64 . Because of non-stationarity in the series, the first differences were taken and the acf and pacf of the differenced series(Figs. IV.65 and IV.66) did not apparently show any significant correlations. However, the autocorrelation at lag 1 was just above the warning level of 1.6 (Pankratz *op.cit*). Although, the trends in the acf and pacf suggest a random walk model (ARIMA (0,1,0)), an AR(1) process was also tried. The values of the criteria are given in the following table.

Model	AIC	SBC	MAE	RMS
ARIMA(1,0,0)	246.75	249.87	6.363	8.634
ARIMA(0,1,0)	237.21	238.73	5.812	7.805

From the above table it is very clear that the random walk model fits the series well, suggesting that the first differences in the catches are randomly fluctuating. In this case the acf of the residuals is same as that of the acf of the first difference.

IV.4.3.3 Penaeid prawns

The landings of penaeid prawns comprising multiple species varied between 1.85 thousand tonnes in 1961 to 28.04 thousand tonnes in 1995 with a peak of 30.18 thousand tonnes in 1994(Fig IV.67).

From the trend in the landings and also from the acf and pacf(Figs IV.68 and IV.69) plots it is clear that the series is non-stationary and needs differencing. The acf and pacf of the first difference (Figs IV.70 and IV.71) suggested that the series of the first differences to be stationary. The pacf cuts off after lag 2 and acf cuts off after lag 1 and thus an ARIMA(2,1,0) was tentatively identified. The acf of the residuals (Fig IV.72) revealed that none of the autocorrelations were significant and the identified model seemed to be adequate(Fig IV.67). The estimated autoregressive coefficients were -0.4518 and -0.4341 respectively with a constant term of 0.746.

IV.4.4 Maharashtra

IV.4.4.1Total

The total marine fish landings in the state varied from 1.162 lakh tonnes in 1961 to 3.165 lakh tonnes in 1995 , with the peak landings in 1991 from which there is a downward trend in the catches.(Fig IV.73).

The acf and pacf of the landings and the trend in the landings indicated that the series is non-stationary(Figs IV.74 and IV.75). The acf and pacf of the differenced series(Fig IV.76 and IV.77) revealed that none of the auto correlations were significant according to the test criterion(Box-Ljung Q- statistics). Thus differencing tended to reduce the series of the total landings to a random walk process. However, following the guidelines of Pankratz(*op.cit*) an ARIMA(0,1,1) was also suggested by the acf and pacf plots. The values of the criteria are given in the following table.

MODEL	AIC	SBC	MAE	RMS
ARIMA(0,1,0)	328.74	330.27	23.058	29.988
ARIMA(0,1,1)	327.06	330.12	22.202	28.755

Thus from the above table that ARIMA(0,1,1) was found to fit the data better and the acf of the residuals (Fig IV.78) conforms to white noise process. The fitted curve is given in Figure IV.73.

IV.4.4.2 Penaeid prawns

The penaeid prawn landings ranged from 8.24 thousand tonnes in 1961 to 40.45 thousand tonnes in 1995 with a low of 5.19 thousand tonnes in 1963 and a peak of 58 thousand tonnes in 1992(Fig IV.79). The acf and pacf of the landings(Figs IV..80 and IV.81) and the trend in the landings indicated that the series was nonstationary and perhaps needed differencing. The acf and pacf of the first difference are given in Figs(IV.82 and IV.83) and from that it is observed that the differenced series could be stationary. Although the autocorrelations at the lower lags were not significant , the lags at 6 and 10 were significant. Initially, a random walk model ARIMA(0,1,0) was tentatively identified. However the significant periodic lags were suggestive of a seasonal model and tentatively an ARIMA$(0,0,1)(2,1,0)_6$ was identified based on the autocorrelation functions. The values of the selection criteria are given below.

MODEL	AIC	SBC	MAE	RMS
ARIMA(0,1,0)	248.12	249.65	6.99	9.16
ARIMA(0,0,1)$(2,1,0)_6$	237.48	242.06	5.06	7.13

The acf of the residuals (Fig IV. 84) exhibited a white noise process and the Box-Ljung Q- statistics was not significant. The fitted curve is given in Fig IV.79.

IV.4.4.3 Bombayduck

It is an important pelagic resource of the state; whose landings reached a peak of about 82 thousand tonnes in 1981. However from 1991 that year onwards then was general declining trend reaching a low figure of about 13 thousand tonnes in 1995 (Fig IV.85). The acf and pacf are given Figs IV .86 and IV .87. The acf and pacf the first differenced series(Figs IV.88 and IV.89) showed however none of the auto correlations was significant, suggesting the first difference on the estimated landings fluctuated randomly with a constant mean. It may be noted that the acf and pacf of the original series may also prompt tentatively to select as AR(1) process.

The values of the selection criteria for the models were:

MODEL	AIC	SBC	MAE	RMS
AR(0,1,0)	273.206	274.73	9.154	13.251
AR(1,0,0)	278.225	284.33	9.233	12.844

Although the RMS for AR(1) was lower, the other three criteria strongly favoured the random walk model, hence, it was selected to describe the landings and the fitted curve is given Fig. IV.85.

IV.5 Oilsardine And Solar Activity

The Indian oilsardine (*Sardinella longiceps*) is one of the most commercially important pelagic fin fish resources occurring in the Malabar coast. Like the pelagic fish communities of other upwelling coasts that include a sardine, an anchovy and a mackerel, the pelagic fish assemblage of the Malabar coast has suffered wide fluctuations in the abundance of the individual components of which oilsardine is an important and significant resource. The variability in oilsardine was noted as long back as in 1865 which prompted Day not to advocate a planned industrial expansion based on oilsardine fishery. The variability in the landings of oilsardine continues to baffle the research workers.

Of late, the oilsardine fishery along the west coast especially along the Kerala and Karnataka coast is causing concern showing signs of declining trend coupled with its year to year variability. The biological characteristics of the oilsardine stock have been thoroughly researched and well documented. Attempts were also made to evaluate the effect of fishing and estimate the stock size. However, the stock assessment studies have revealed no more information on the stock than is available and some of the studies have given conflicting harvesting options depending upon the data series. Some workers have also tried to explore the periodic or cyclic variability in the oilsardine stock in the context of physical, chemical and biological oceanographic parameters either singly or in combination with the climatic and other ocean related phenomena.

In this study an empirical model is given to describe the oilsardine fishery along the Kerala coast using the time series approach and also examine its relationship with the solar activity. A brief review of the literature on fishery and stock assessment of oilsardine , effect of fishery independent factors on its variability is given hereunder. Some related works on the stocks of other pelagic populations elsewhere are also briefly reviewed.

IV.5.1 Studies on oilsardine

Many research works were carried out on the fishery and biology of the oilsardine since early 50's. However only the recent works on these aspects are indicated below as the references to earlier works could be obtained from them. Kurup *et.al.*(1989) carried out the stock assessment of the oilsardine along the west coast of India. In their paper they have referred to earlier works on oilsardine fishery and biology. Using the data from 1979-83, they estimated the growth parameters and the mortality rates. They gave no information of the stock size and refrained from assessing the effect of fishing on the exploited stock. They contended that improvements of data collection and collation systems will be necessary for future analysis.

Annigeri *et. al.* (1992) have also attempted a similar study but based on a larger data base. They also a gave review of earlier work done on the fishery and biology of oilsardine. They also estimated the vital parameters of the population and assessed the effect of fishing on the stock. They found that there was scope to increase the annual catch however do not recommend increase in fishing effort.

Longhurst and Wooster (1990) gave a detailed account of the oilsardine fishery and also studies related to the effect of fishery independent factors on the oilsardine variability. They observed that oilsardine landings data clearly included decadal trends. According to them the cyclic pattern of oilsardine probably reflected density dependence rather than response to fishing. While explaining the physical and environmental variables which could have caused the variations in the oilsardine landings they have established a relationship of variations in the mean sea level with fluctuations in the abundance.

Madhupratap *et.al.* (1994) while disagreeing with some of the observations of Longhurst and Wooster (*op.cit.*) questioned the validity of the precision of the data of the earlier period and also the observed relationship. They also stressed the importance of impact of climatic and other ocean related parameters on the oilsardine stock. They outlined a possible research approach in tackling the problem.

IV.5.2 Ocean parameters and solar activity

Effect of some of the physical parameters such as the sea surface temperature, El Nino activity, upwelling and solar radiation on the fisheries of some exploited stocks has also been studied since long.

Regner and Gacic (1974) concluded that in sardine catch and solar activity the most significant were the periods of about 11 years. Long-term fluctuations of the sardine catch on the eastern Adriatic coast could be approximated by the sum of harmonics which includes the 11 year cycle also.

Kowalik and Wroblewski (1973) as quoted in Regner and Gacic (*op.cit.*) have found that the long term changes of the Baltic sea level show the characteristic period of 11 years which was connected with the solar activity.

Southward *et.al.*(1975) subjected the annual mean SST's of a certain station in the English channel to spectral and auto correlation analysis. The study revealed the presence of major cycles of order of

10-11 years but longer and shorter harmonics were also present. Filtering of the shorter periodic variations by 5 year running averages brought out 10-11 year cycle very well and illustrated close agreement with curves of annual mean sunspot numbers. Similar results were obtained for number of pilchard eggs in the plankton, the catch of demersal fishes and proportion of barnacle species in the intertidal zones.

Driver (1978) analysed the annual landings of shrimp (*Crangon crangon*) in the Lancashire and Western Sea Fisheries District (UK) and found the abundance of shrimp to be correlated with mean sunspot number.

Maximov *et.al.* (1972) found out a phase relationship between the sea surface temperature and the sunspot activity.

According to Love and Westphal (1981) Dungeness crab catches and sunspot numbers both varied in approximately 11 year cycle. They observed that peak catches of some years closely corresponded with the sunspot maximum years. High sunspot numbers in a particular year seemed to be a predictor of relative low crab catches five years hence.

Reid (1987) analysed the influence of solar variability on global sea surface temperature. The secular variation in globally averaged SST over the past 130 years has been found to show a certain amount of similarity to the corresponding variation of the solar activity as revealed by the envelope of the 11 year sunspot cycle.

Li Zigiang and Ma Shengchun (1995) observed a relationship between El Nino events and 11 year solar cycles.

Chen *et.al.* (1994) investigated the roles of vertical mixing ,solar radiation and wind stress in a model simulation of the SST seasonal cycle in the tropical Pacific ocean. It was found that the large SST annual cycles in the eastern equatorial Pacific is to a large extent controlled by the annually varying mixed layer depth which inturn is mainly determined by the competing effects of solar radiation and wind forcing. The SST seasonal cycle in the Western equatorial Pacific basically follows the semi annual variations of solar activity.

Shevnin(1994) found significant correlation between the solar and magnetic activities with the Caspian sea level.

Terauchi *et.al* (1991) while explaining environmental factors for variations in the stock of Yellowtails in its Pacific sub-population observed that periods of peak catches correspond to the minimum point in the sunspot number.

Kawasaki and Omori (1988) suggest that the variations in solar radiation lead to variation in primary productivity and therefore in availability to sardines of suitable food item.

Anderson (1989) documented apparent correspondence between sunspot cycles on both eastern Pacific SST departures and El Nino frequency and intensity. This would imply that there is some threshold level of solar input which affects (modulates) the ENSO process and below which level the sunspot frequencies is nearly irrelevant to the apparently inherent upper ocean temperature changes around the Pacific Ocean.

Sharp and Csirke (1984) reviewed many of the world's neritic resources variations and their relationships to climate-driven physical processes. Decadal scale trends in some of the climatic parameters were found to influence the cyclical patterns observed in some fisheries.

Kawasaki (1991) observed that three sardine populations in the Pacific Ocean and the European pilchard in the North Atlantic have undergone long-term coincident change in their abundance while the pacific and Atlantic herrings also do so with a phase different from that of the sardine populations. He also observed a high positive correlation between trends in abundance of the sardine populations and a secular change in anomaly of the global mean surface temperature. He concluded ***We are perhaps now standing at a turning point for the structural change in the pelagic fish community in the world ocean which may be caused by a global climatic change*** .

Rothschild (1991) gave detailed account on the causes for variability of fish population. He observed that to circumvent the difficulty it is necessary to understand the relationship between population dynamics and the physical environment as the most fundamental.

IV.5.3 Time series modelling and relationship with solar activity

Modelling the fish catches through the time series approach especially of Box-Jenkins type is already discussed and presented in the earlier section. The harmonic time series analysis has been considered in the present case in analysing the time series data of the oilsardine.

If the observations tend to show strong cyclical or periodic variations it is tempting to fit a model with sine and cosine terms(Saila *et.al.* 1980). Although harmonic regression analysis has been widely used in agriculture and other ecological studies its applications to fisheries has been minimal. Bulmer (1974) applied harmonic analysis to the 10 year cycles of Atlantic salmon. Saila *et.al.* (1980) analysed the 12 year monthly average catch per day fished of rock lobster from the New Zealand using the harmonic regression. They concluded however an ARIMA model was found to be most suitable in terms of providing forecasts upto 12 months ahead. The conclusion was based on the lower standard deviations for residuals as compared to the other methods used in their study.

Stergiou and Christou (1996) evaluated eight forecasting techniques on the basis of their efficiency to model and provide accurate operational forecasts of annual commercial landings of 16 species or groups of species in Hellinic (Greek) marine waters. The results revealed that the harmonic regression and multiple regression models outperform other models such as ARIMA, vector auto regression and exponential smoothing. ARIMA models were not found among the best performers because the yearly data were not characterized by strong autocorrelation lags of greater than 1 year. Because of this , ARIMA could not possibly recover ample information from the data and this necessitated application of other techniques such the harmonic regression to the data which yielded satisfying results.

Before attempting the harmonic analysis a clear cyclic pattern should be identified. Sometimes there may be some embedded minor cycles also. However when the underlying pattern is obscured by noise as is the case with that of fisheries data, non-linear data smoother provide a practical method of providing smooth traces of data confounded with probably long tailed or occasionally ***spikey*** noise. Velleman (1980) proposed a suite of data smoothers of which the technique of 4253H exhibited best characteristics. This smoothing starts with a running median of 4 which is centred by a running median of 2. It then resmoothes the values by applying a running median of 5, a running median of 3 and hanning(running weighted average). Residuals are computed by subtracting the smoothed series from the original series. The whole process is repeated on the computed residuals. Finally, the smoothed residuals are added to the smoothed values obtained first time through the process.

In this section an attempt is made to identify the possible cyclic pattern in the landings of oilsardine and carry out harmonic analysis for modelling the catch.

In the earlier section, the oil sardine landings in Kerala were identified to be a multiplicative seasonal process and also an AR(0,1,0) process was also found to be a probable candidate. According to Pankratz (*op cit*) "not every ARIMA model with significant estimates is a suitable one.... We strive for parsimonious models which fit the data adequately with significant coefficients but we should also temper on statistical results with insight into the nature of the underlying data". Stergiou and Christou (*op.cit*) pointed out that ARIMA models were not found among the best performers because the yearly data were not characterized by strong auto correlations. Because of this, ARIMA could not possibly recover ample information from the data and this necessitated application of other techniques such as the harmonic regression to the data which yielded satisfying results.

In the light of the above remarks, the data on oil sardine landings in Kerala was further explored. The reason for selecting Kerala data is obvious. The landings in the state have contributed a major share to the total landings and also the fishery had shown wide fluctuations, with almost decadal cycle (Longhurst and Wooster *op.cit*). Besides in the east coast it is only in very recent years it is emerging in good quantities but not good enough to be a significant contributor to the total landings of the states of Tamilnadu and Andhra Pradesh. In this section harmonic regression analysis of oil sardine landings of Kerala is carried out and compared the results with those obtained in the earlier sections. Also, the possible causes in variations in the oil sardine landings was explained with the help of solar activity represented by the average annual sunspot members. The data pertaining to 1961-94 was used for analysis. The data on solar activity was obtained from NOAA, USA via Internet.

The smoothed data, along with the general trend line and the unsmoothed data on the landings are plotted (Fig.IV.90). The mean annual sunspot activity was also drawn on the same graph. The following observations could be made from the graph.

- There was a general declining trend in the landings as evidenced by the trend line (straight line in the figure.).
- The smoothed data (dotted lines) showed periodicity of about 10 to 11 years.

- Although the years of higher sunspot activity, in general, coincided with higher oil sardine landings, there seemed to be "leads" in the landings with respect to the sunspot activity.

Thus, it was obvious from the above observations the data smoothing algorithm did, in fact, help in highlighting the underlying the periodic trend. It was observed that the periodic trend was confounded with the linear trend in the original series. To get a clearer picture, the data was detrended to determine the periodicity. The declining trend in the landings may also be due increase in fishing effort since 1961. Thus, indirectly, the effect of fishery dependent factor(fishing effort) is removed from the series. Implicitly , it is assumed that the trend in fishing effort since 1961 is approximately linear.

A straight line relationship with time was to fit the data better as determined by r^2 value(0.279). The second degree polynomial did not significantly contribute to r^2(0.293).

. The series was detrended by subtracting the expected values of the fitted line from the observed values.

To determine the periodicity the residuals (the detrended series) was subject to spectral analysis. The periodogram and the spectral density of the residuals with a window width of 5 are given in Figures IV.92 and IV.93. These figures showed evidence of significant periodicity of 11 years and 6 years.

Thus there was justifiable ground to carry out harmonic analysis with linear trend on the oil sardine landings of Kerala.

Initially, only 6 year periodic terms along with linear component was considered which yielded R^2 value of 48.06%. Inclusion of only 11 year periodic terms with a linear trend yielded R^2 of 51%.

By adding the 6 year and 11 year periodicity with linear trend yielded a R^2 of 64.6%. Thus the fitted equation was

$$\mathbf{y = 191.365 - 3.782\,t - 36.196\cos(2\pi t / 11) - 31.437\sin(2\pi t / 11)}$$

$$\mathbf{- 1.707\cos(2\pi t / 6) - 17.273\sin(2\pi t / 6)}$$

Now this model was compared with the proposed ARIMA models indicated in the earlier section with respect to MAE and RMS. The results were indicated in the following table.

MODEL	MAE	RMS
ARIMA(1,0,0)	39.69	49.58
ARIMA(0,1,0)	37.20	53.01
$ARIMA(1,0,0)(1,0,0)_4$	36.66	48.68
HARMONIC REGRESSION	29.50	39.41

Thus Harmonic regression was found to fit the data better as indicated by the lower values of MAE and RMS. Thus, it may be concluded that the oil sardine landings of Kerala could be explained reasonably accurately with a periodic function embedded with a declining linear trend. The fitted harmonic regression curve along with the observed value and the seasonal ARIMA are plotted in Fig IV.91.

The relationship of sunspot activity with oil sardine landings were studied with cross correlation function and cross spectra.

The cross correlation of sunspot activity with oil sardine indicated that, although higher landings seemed to occur during higher solar activity, the sunspot activity was found to lead the oil sardine landings. This meant that higher sunspot activity at present might lead to higher oil sardines in 4 to 6 years hence (Fig. IV. 94)

The ccf of the residuals of linear trend (detrended data) with sunspot activity (Fig.IV.95) however indicated a strong correlation at lag 0 and here also the " lead" effect was observed.

The cross spectra of residuals of the linear trend with sunspot activity exhibited a significant periodicity of 11 years(Fig IV.96).

These analyses indicated that the oil sardine landings or abundance of oil sardine along the Kerala coast displayed a significant 11 year cycle which corresponded with that of the 11 year solar activity, Hence, it may be conclude that the abundance of oilsardine along the Kerala coast ,perhaps, is governed by the solar activity. The general declining trend in the landings may be attributed to the increase in the fishing effort since 1960's. In combination with periodic fluctuation in the abundance, probably caused by periodic variation in the recruitment. The periodic variation in recruitment might have been induced by factors dependent on solar activity.

The investigator could not find any similar study conducted in the context of marine fish landings in India and thus this study could be considered as forerunner to ensuing in depth research.

The observations made and conclusions drawn in this study, however, are in close agreement with the studies conducted elsewhere as cited in the review of literature.

The mechanism or process of interaction of oilsardine abundance (or landings) along the Kerala coast and the solar activity is too complex to explain and surely it is not a direct process. Oilsardine abundance, typical of pelagic stocks elsewhere in the world is governed by not only fishery dependent factors but also by various fishery independent factors. Some of the factors such as the sea surface temperature or El Nino phenomenon might be directly or indirectly influenced by the 11 year solar activity. This in turn would have induced a 11-year cycle in the landings. It is believed (Longhurst and Wooster *op. cit*) that oilsardine fishery mainly comprised of 0-year class only. Thus fluctuations in the landings could be ascribed to recruitment variability. The success or failure of the recruitment in pelagic stocks by and large is governed by the environmental factors, the air-sea interactions and the ocean dynamics. The literature cited earlier did have references of relationship of solar activity with the ocean parameters or phenomenon such as El Nino. Thus it may be concluded, solar activity would perhaps serve as indicator of variations in oilsardine fishery in Kerala.

Fig IV.1 Total Landings
All India - ARIMA(1,1,0)

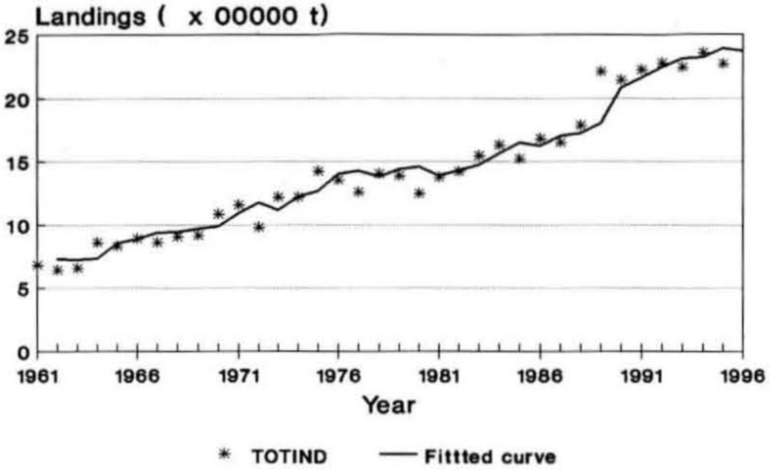


Fig IV.2 Autocorrelation function for
All India Total Landings

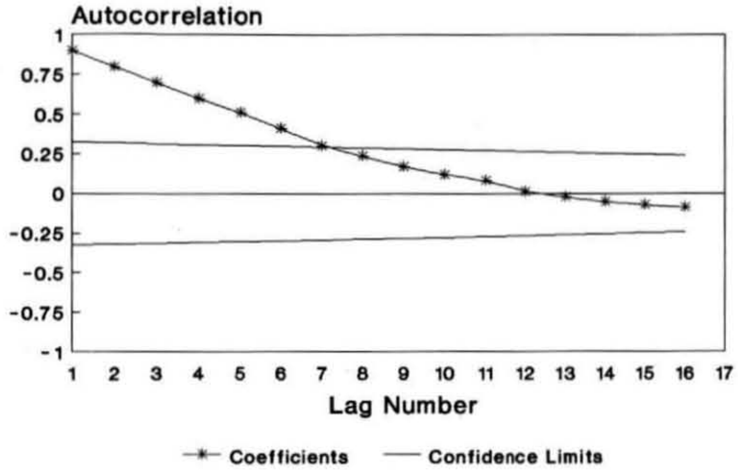


Fig IV.3 Partial Autocorrelations
All India Total Landings

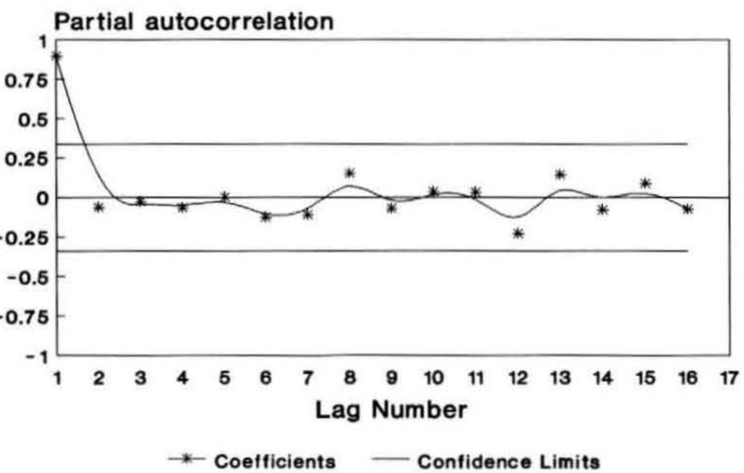


Fig IV.4 Autocorrelation function
All India Total landings
(FIRST DIFFERENCE)

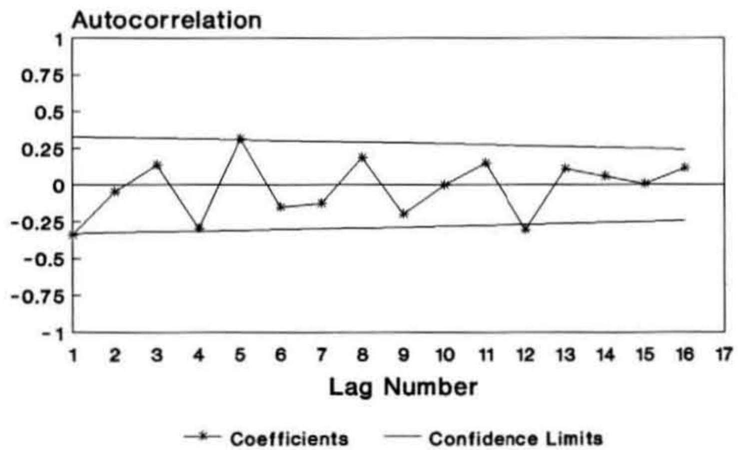


Fig IV.5 Partial Autocorrelation
All India Total Landings
(FIRST DIFFERENCE)

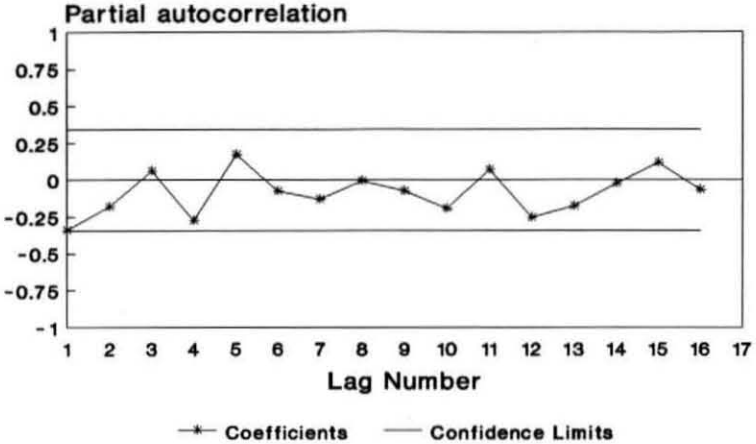


Fig IV.6 Autocorrelation function of
residuals - ARIMA(1,1,0)
(ALL INDIA TOTAL)

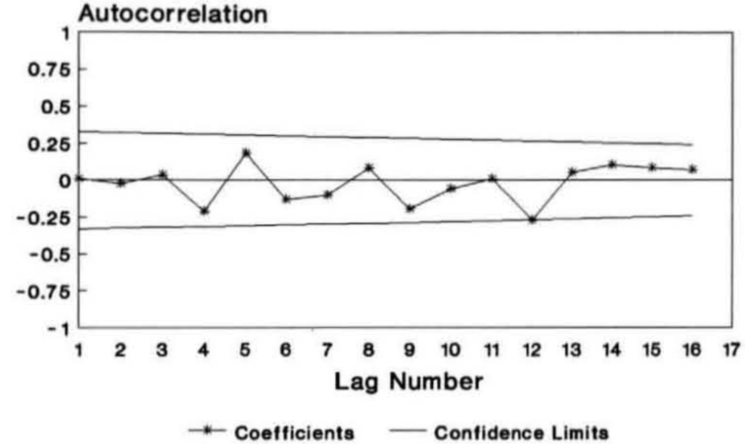


Fig IV.7 Oilsardine - All India
(ARIMA (1,0,0)(0,0,1) 5)

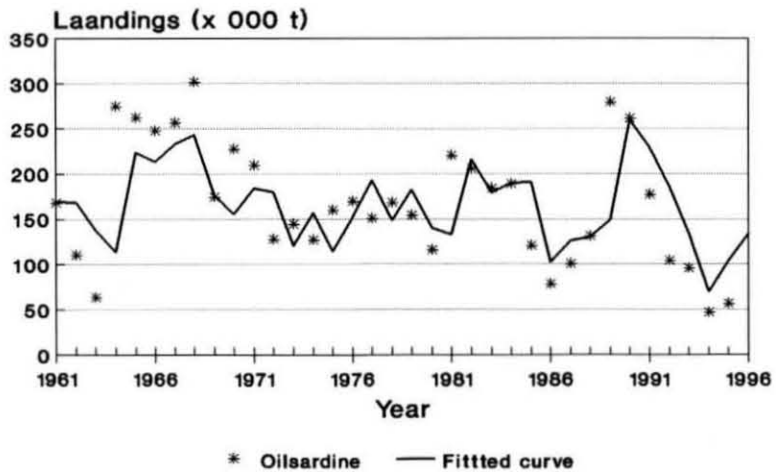


Fig IV.8 Autocorrelation function
Oilsardine - All India

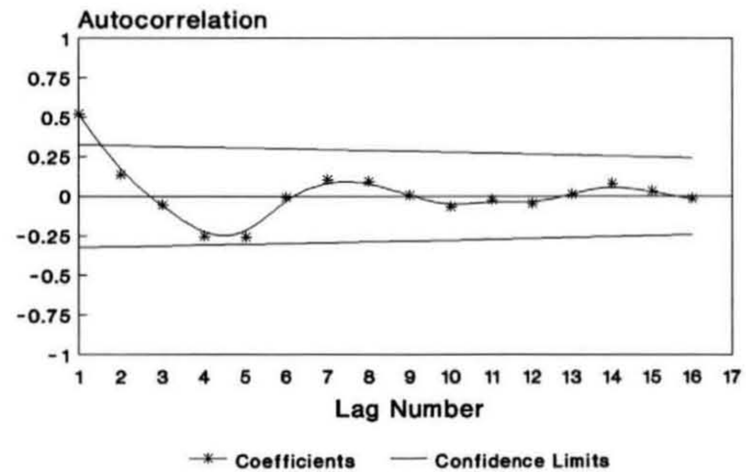


Fig IV.9 Partial Autocorrelation
Oilsardine - All India

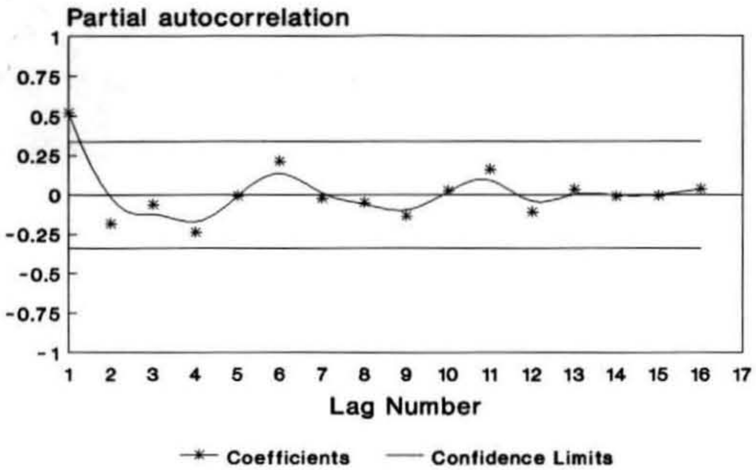


Fig IV.10 Autocorrelation function
Oilsardine - All India
(FIRST DIFFERENCE)

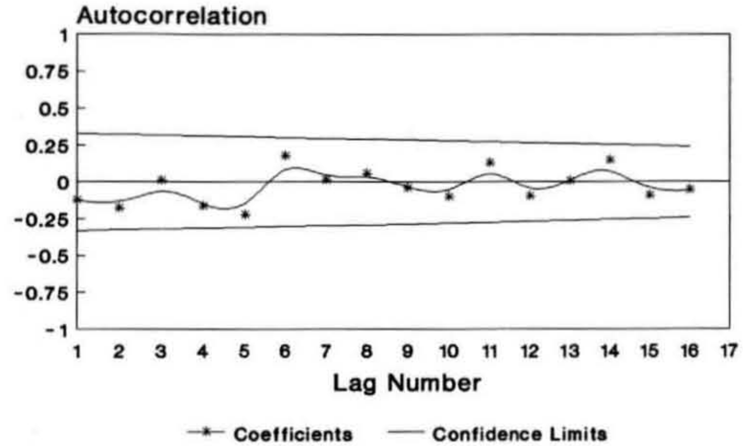


Fig IV.11 Partial Autocorrelation
Oilsardine - All India
(FIRST DIFFERENCE)

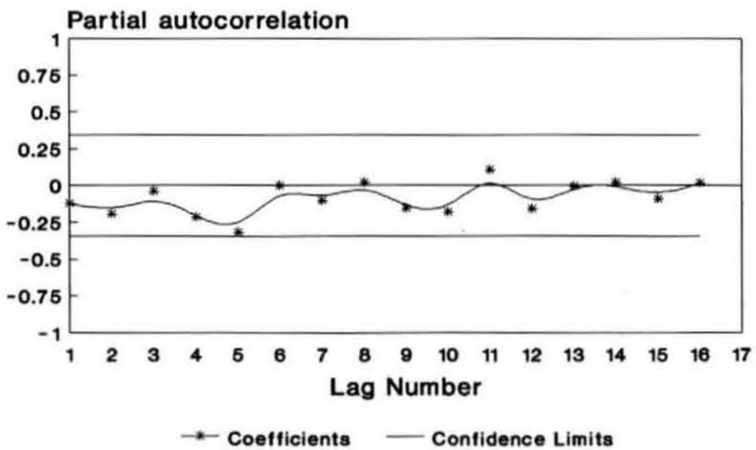


Fig IV.12 Autocorrelation function
Oilsardine - All India
(SEASONAL DIFFERENCE)

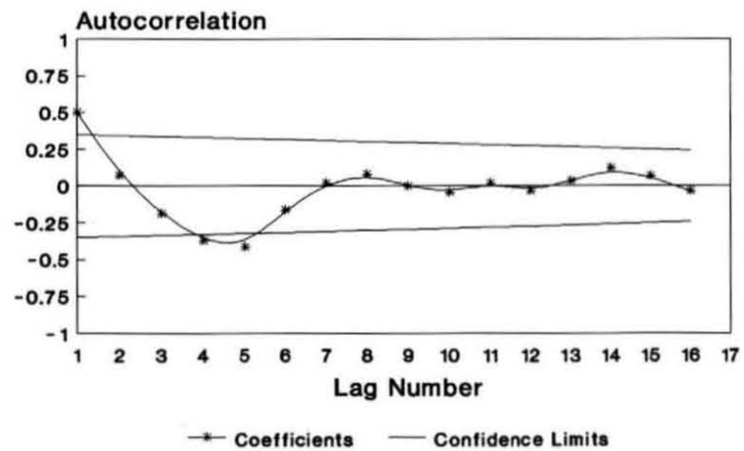


Fig IV.13 Autocorrelation function of
Oilsardine - All India
(RESIDUALS)

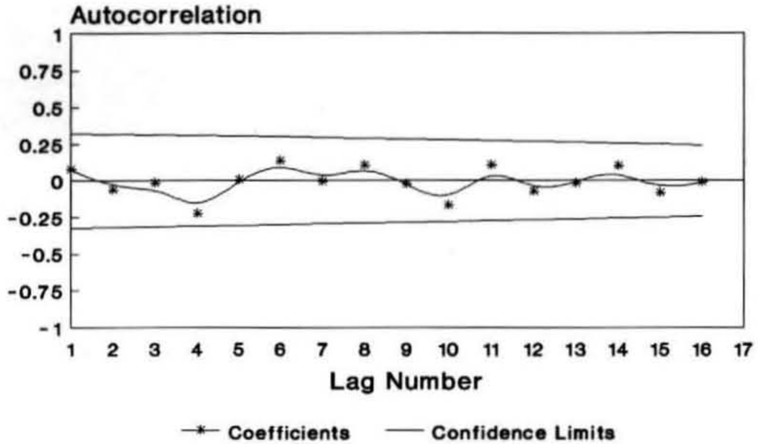


Fig IV.14 Bombayduck Landings-All India
ARIMA(0,1,0)

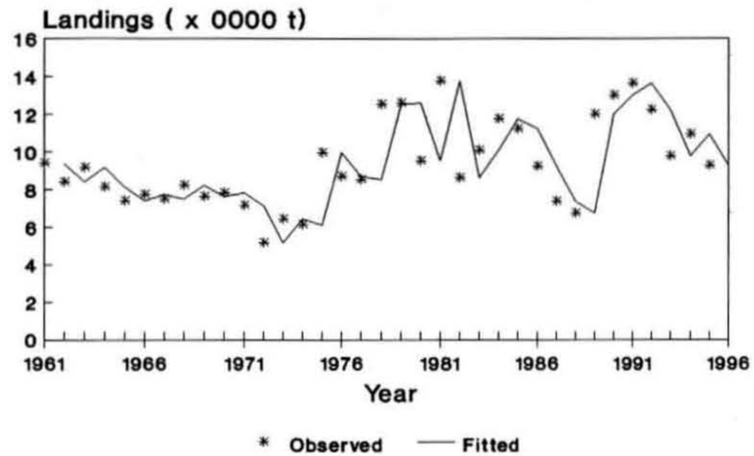


Fig IV.15 Autocorrelation function
Bombayduck - All India

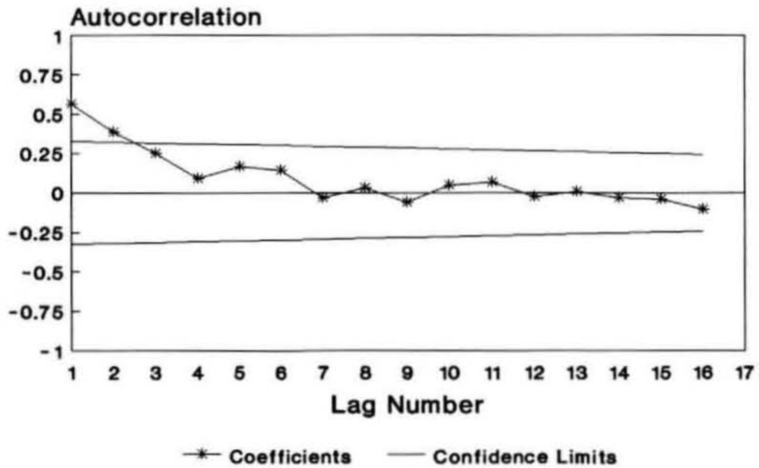


Fig IV.16 Partial Autocorrelation
Bombayduck - All India

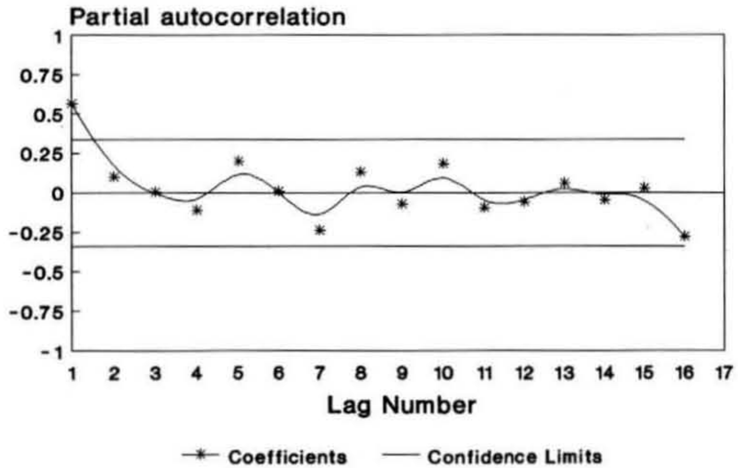


Fig IV.17 Autocorrelation function
Bombayduck - All India
(FIRST DIFFERENCE)

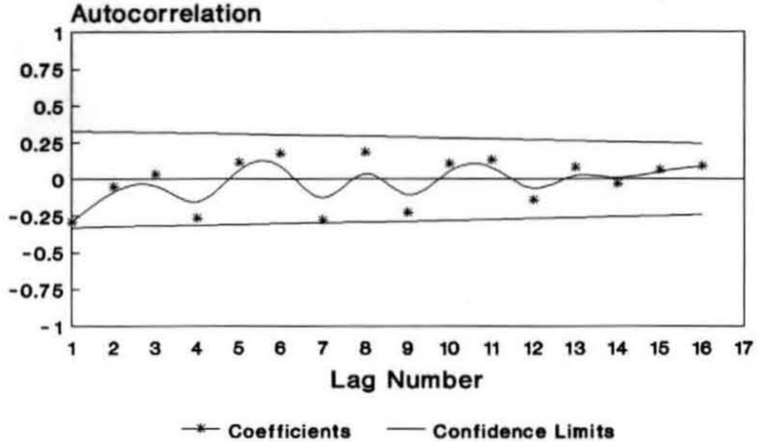


Fig IV.18 Partial Autocorrelation
Bombayduck - All India
(FIRST DIFFERENCE)

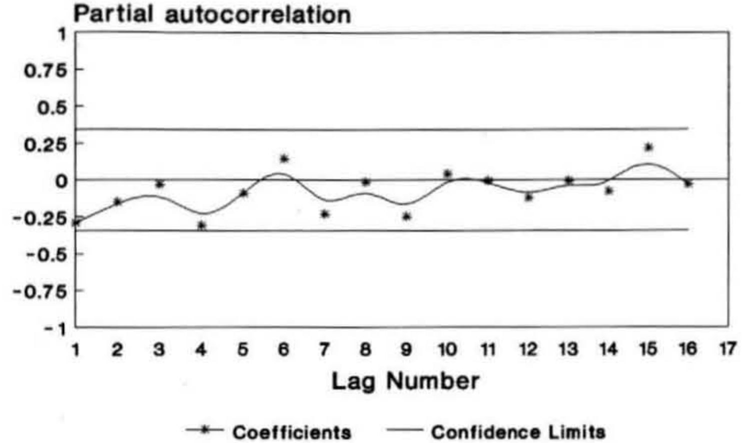


Fig IV.19 Mackerel - All India
(ARIMA(1,0,0))

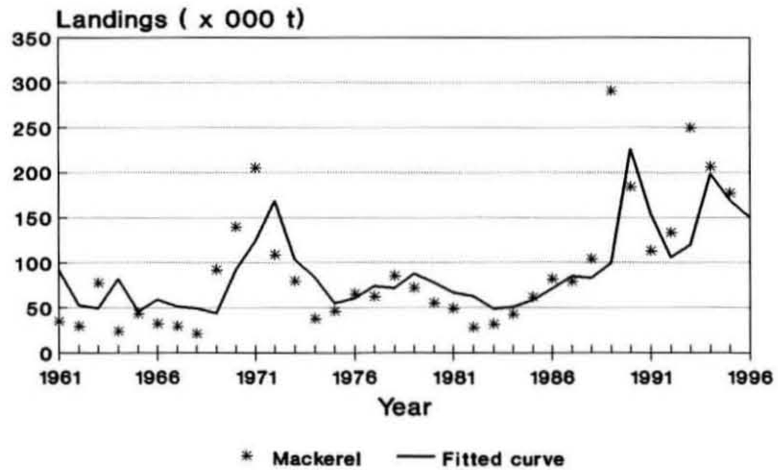


Fig IV.20 Mackerel - All India
(ARIMA(1,0,0)(1,1,0) 4)

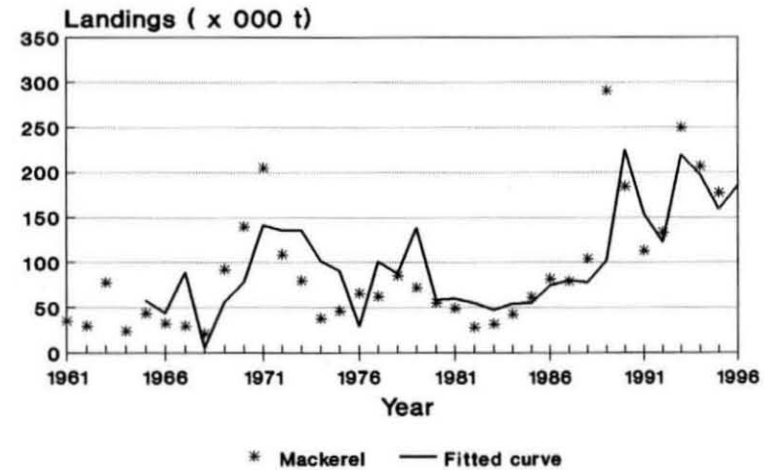


Fig IV.21 Autocorrelation function
Mackerel - All India

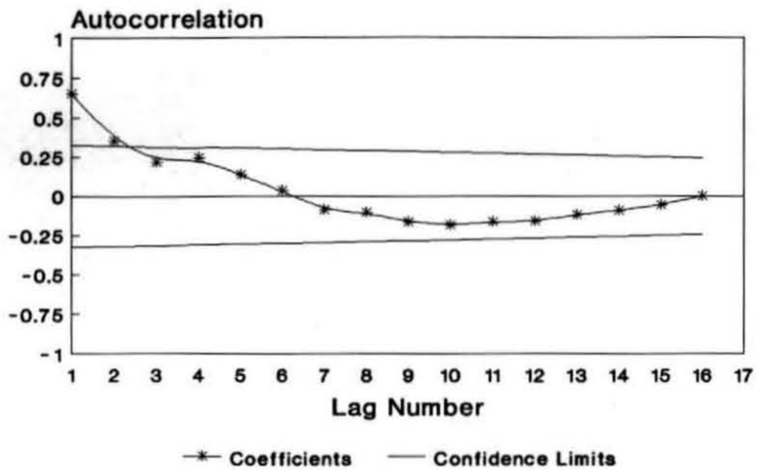


Fig IV.22 Partial Autocorrelation
Mackerel - All India

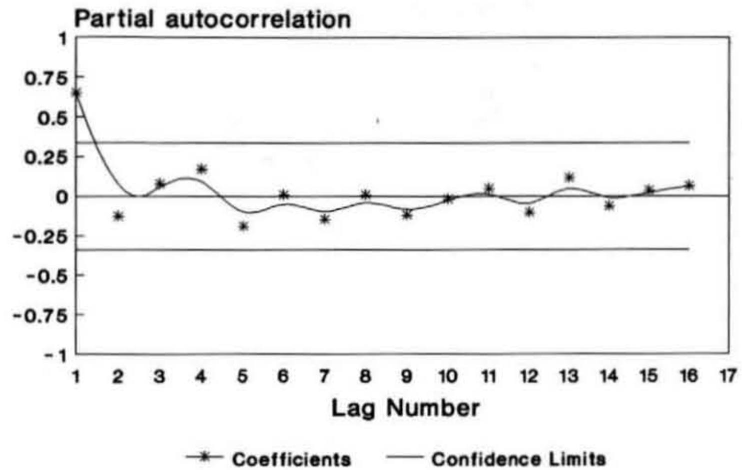


Fig IV.23 Autocorrelation function
Mackerel - All India
(FIRST DIFFERENCE)

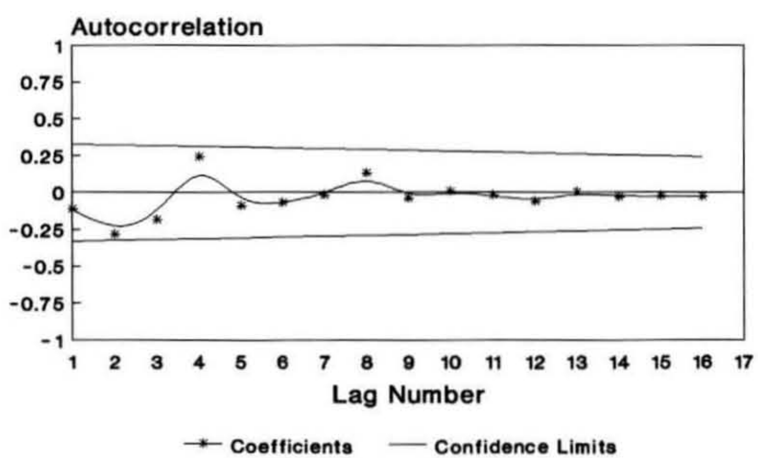


Fig IV.24 Partial Autocorrelation
Mackerel - All India
(FIRST DIFFERNCE)

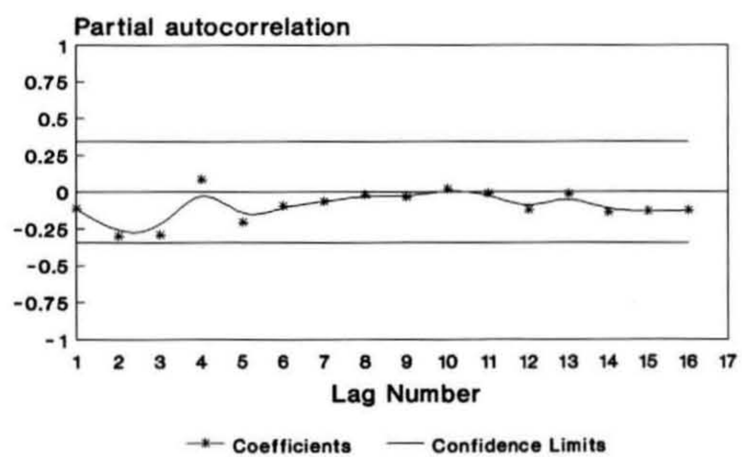


Fig IV.25 Autocorrelation function
Mackerel - All India
(SEASONAL DIFFERENCE)

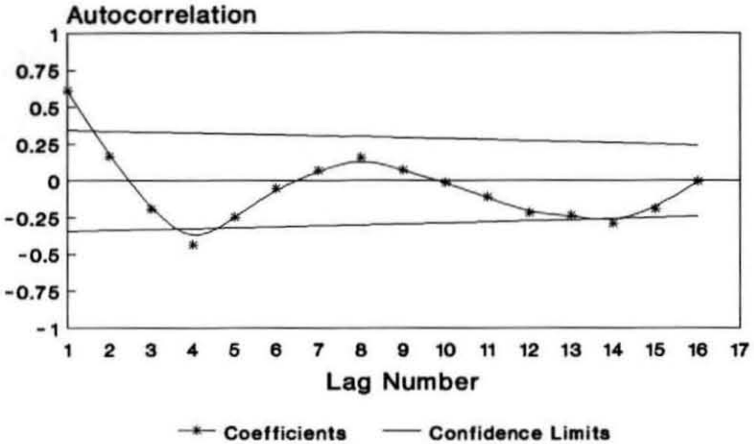


Fig IV.26 Autocorrelation function
Mackerel - All India
(RESIDUALS OF SEASONAL MODEL)

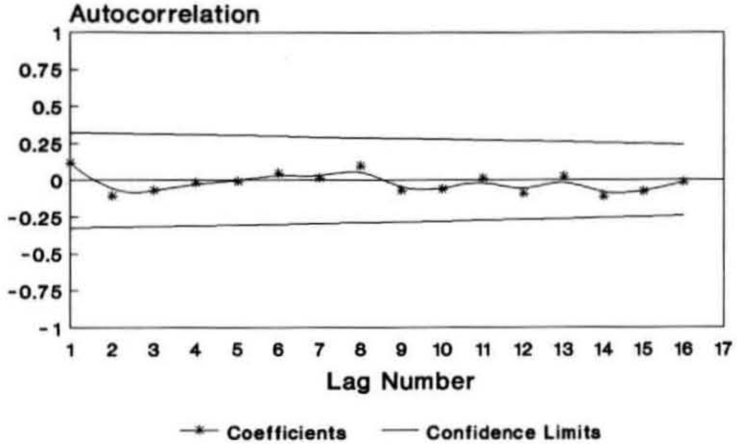


Fig IV.27 Penaeid prawns - All India
ARIMA (0,1,1)

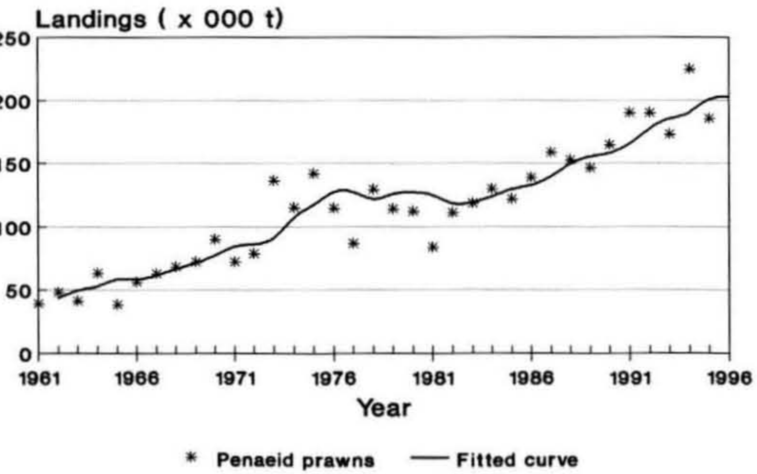


Fig IV.28 Autocorrelation function
Penaeid prawns - All India

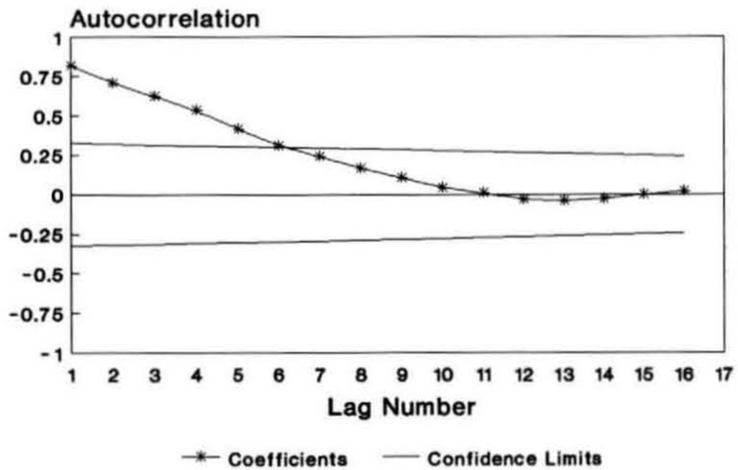


Fig IV.29 Partial Autocorrelation
Penaeid prawns

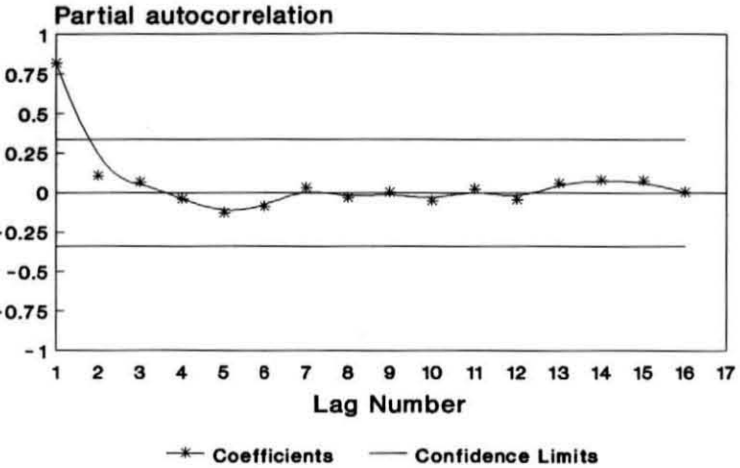


Fig IV.30 Autocorrelation function
Penaeid prawns - All India
(FIRST DIFFERENCE)

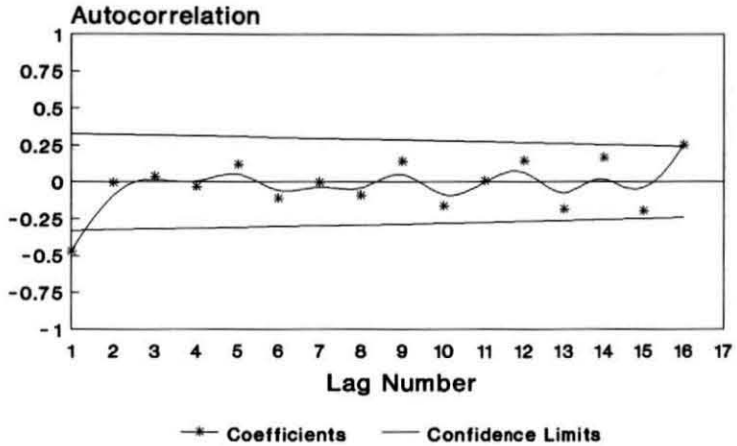


Fig IV.31 Partial Autocorrelation
Penaeid prawns - All India
(FIRST DIFFERENCE)

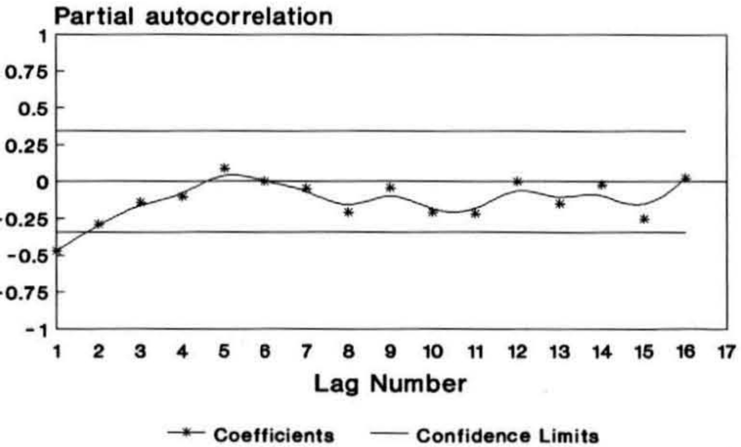


Fig IV.32 Autocorrelation function
Penaeid prawns - All India
(RESIDUALS)

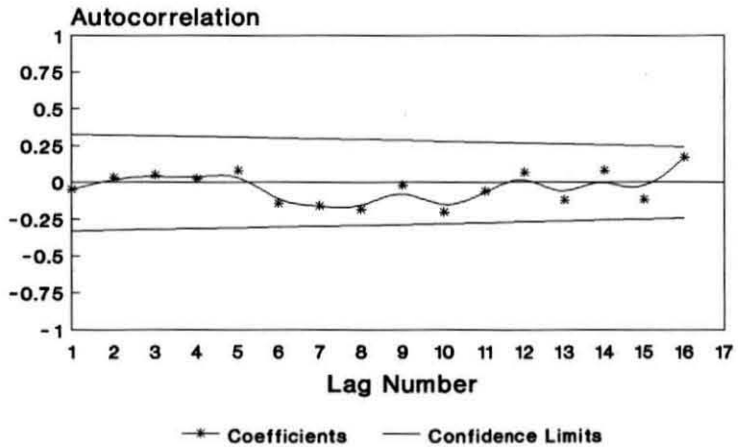


Fig IV.33 Total landings - Kerala
ARIMA (0,1,0)

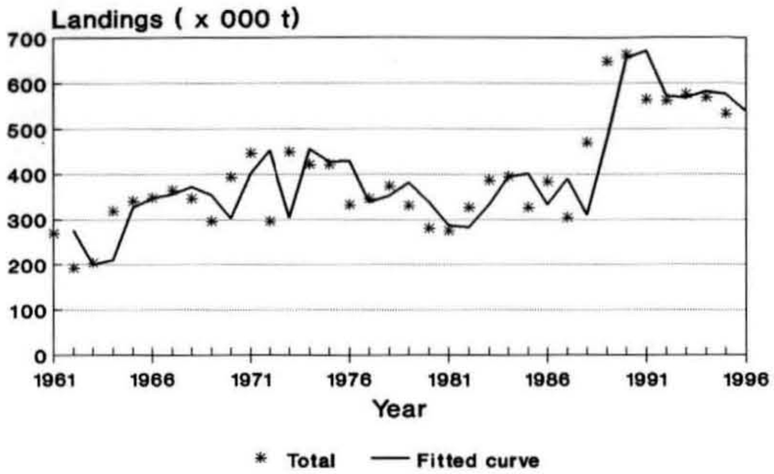


Fig IV.34 Autocorrelation function
Total landings - Kerala

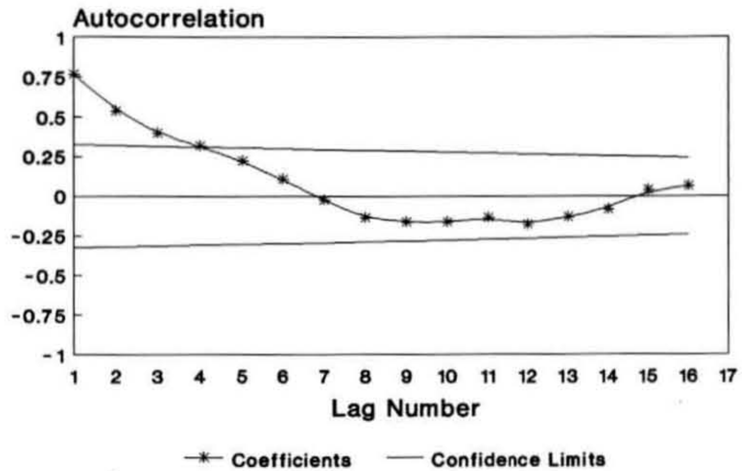


Fig IV.35 Partial Autocorrelation
Total landings - Kerala

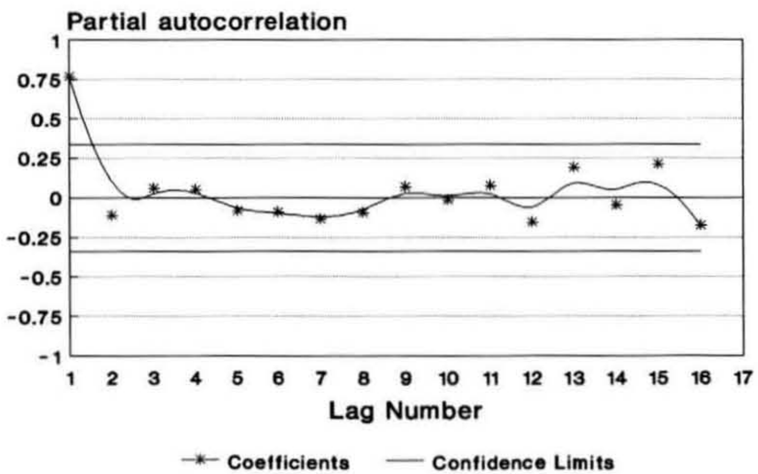


Fig IV.36 Autocorrelation function
Total landings - Kerala
(FIRST DIFFERENCE)

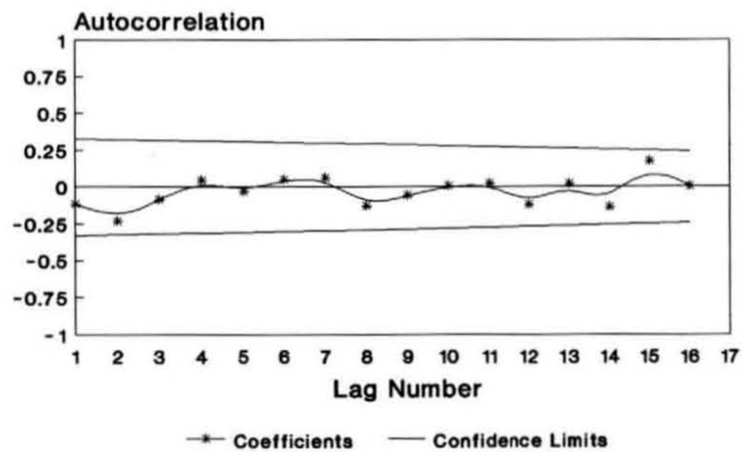


Fig IV.37 Partial Autocorrelation
Total landings - Kerala
(FIRST DIFFERENCE)

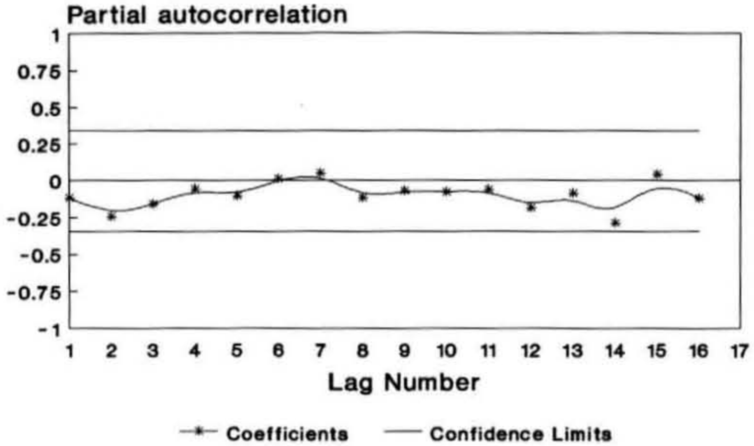


Fig IV.38 Oilsardine - Kerala
(ARIMA (1,0,0)(1,0,0)4)

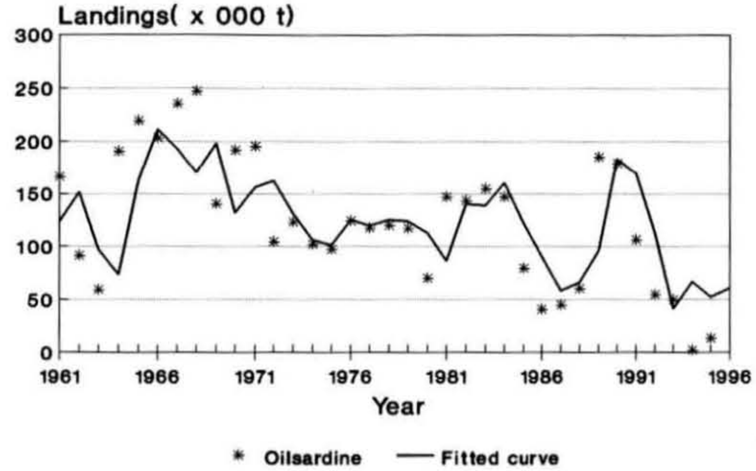


Fig IV.39 Autocorrelation function
Oilsardine - Kerala

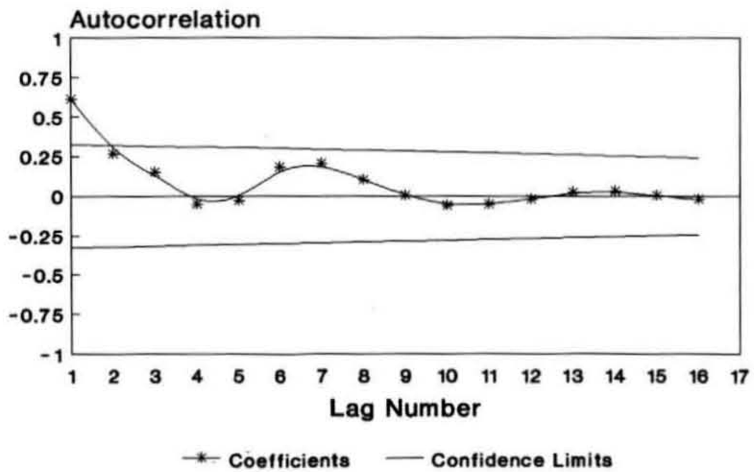


Fig IV.40 Partial Autocorrelation
Oilsardine - Kerala

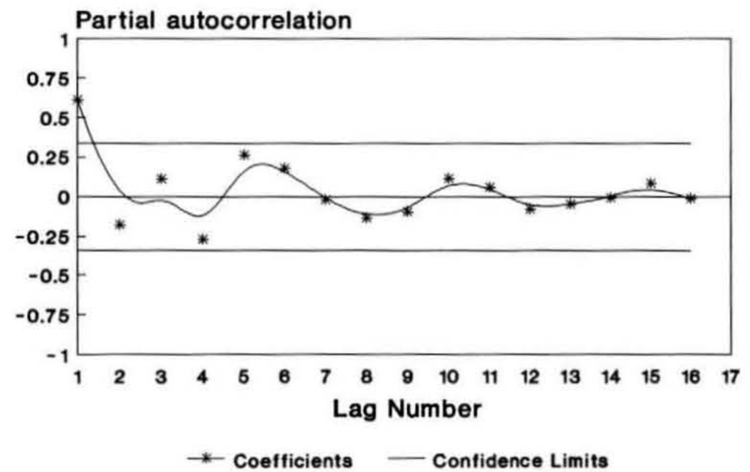


Fig IV.41 Autocorrelation function
Oilsardine - Kerala
(FIRST DIFFERENCE)

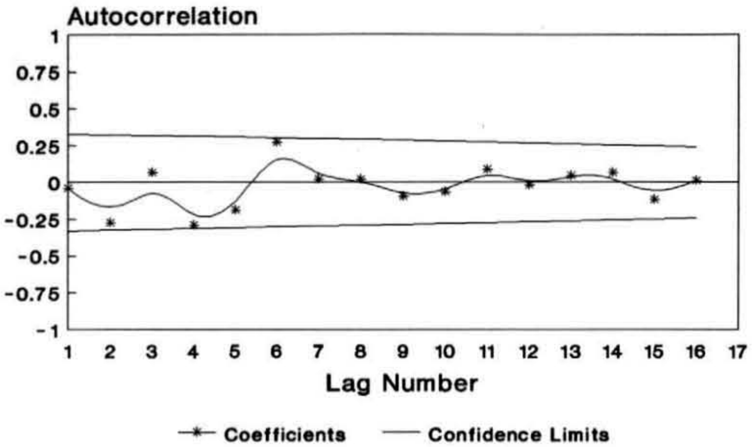


Fig IV.42 Partial Autocorrelation
Oilsardine - Kerala
(FIRST DIFFERENCE)

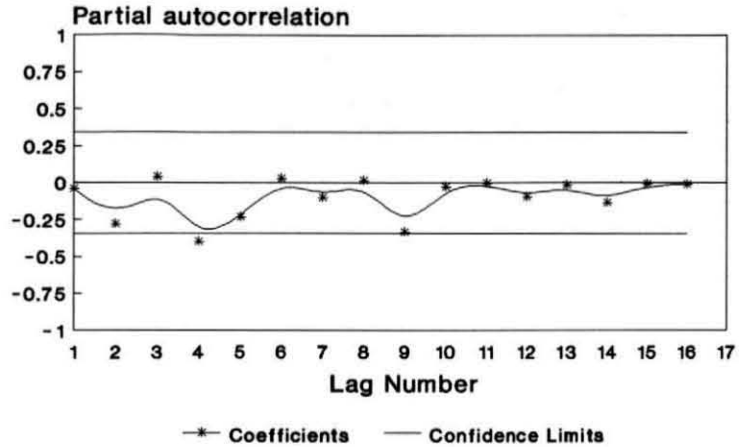


Fig IV.43 Autocorrelation function
Oilsardine - Kerala
(SEASONAL DIFFERNCE 4)

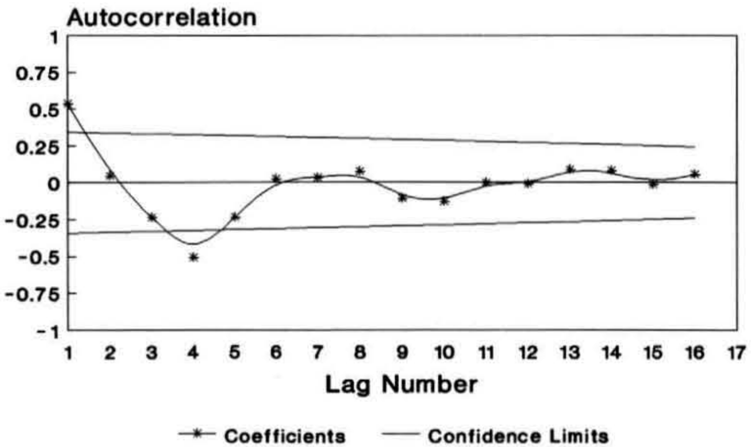


Fig IV.44 Autocorrelation function
Oilsardine - Kerala
(RESIDUALS OF SEASONAL MODEL)

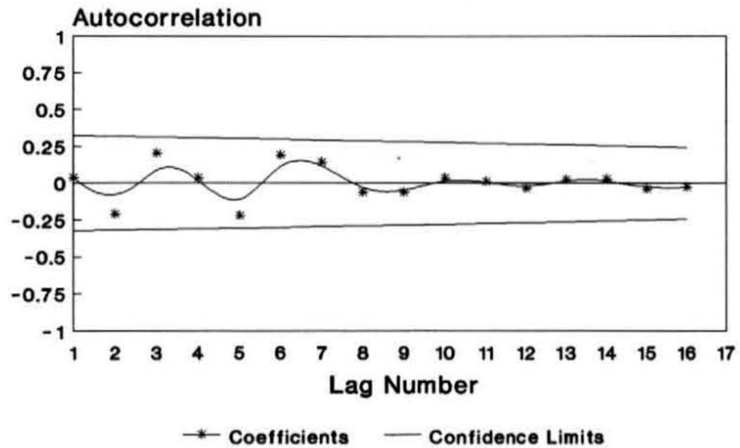


Fig IV.45 Mackerel - Kerala
(ARIMA (1,0,0)(1,1,0)3)

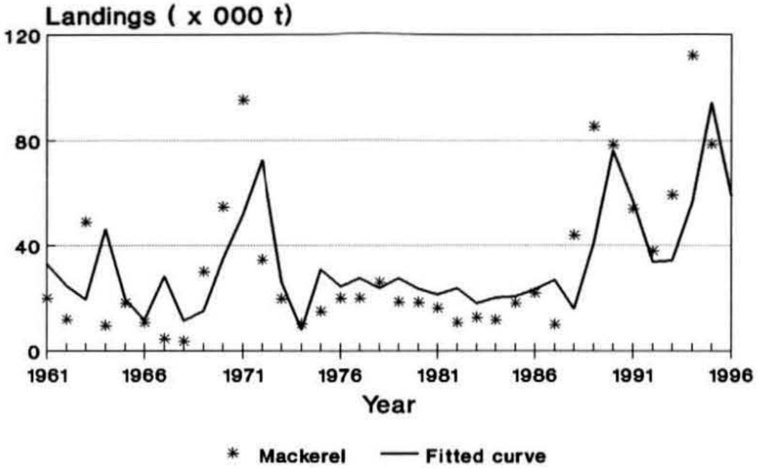


Fig IV.46 Autocorrelation function
Mackerel - Kerala

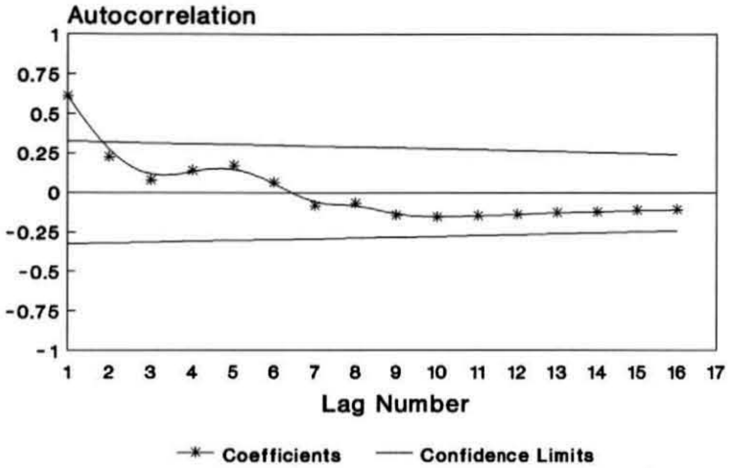


Fig IV.47 Partial Autocorrelation
Mackerel - Kerala

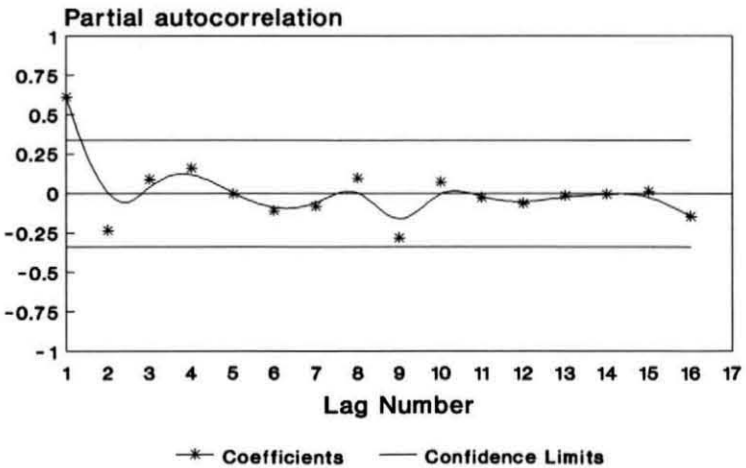


Fig IV.48 Autocorrelation function
Mackerel - Kerala
(FIRST DIFFERENCE)

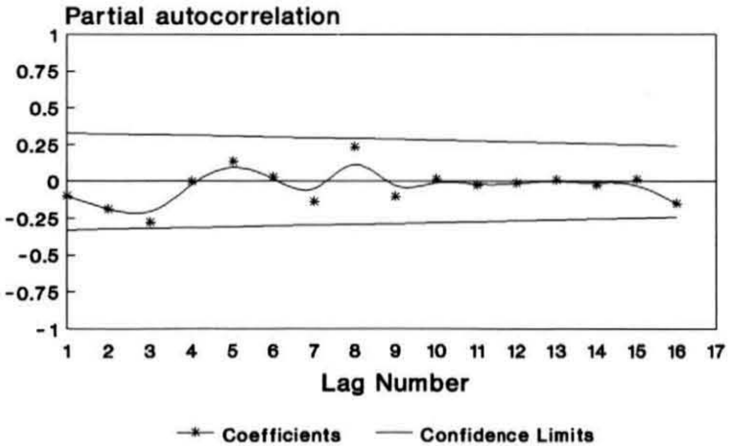


Fig IV.49 Partial Autocorrelation
Mackerel - Kerala
(FIRST DIFFERENCE)

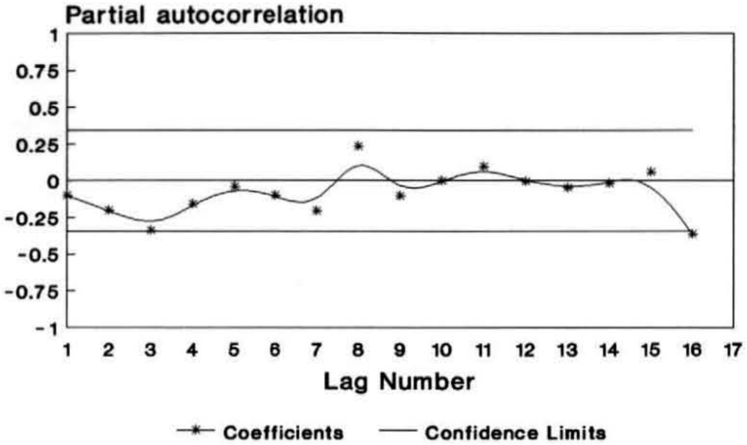


Fig IV.50 Autocorrelation function
Mackerel - Kerala
(SEASONAL DIFFERENCE)

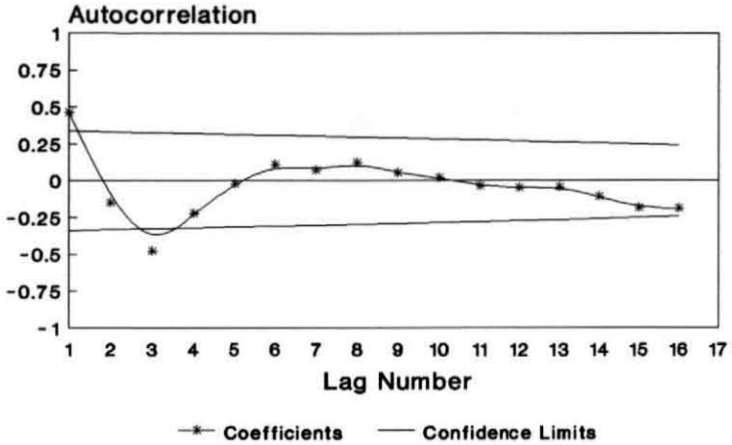


Fig IV.51 Autocorrelation function
Mackerel - Kerala
(RESIDUALS SEASONAL MODEL)

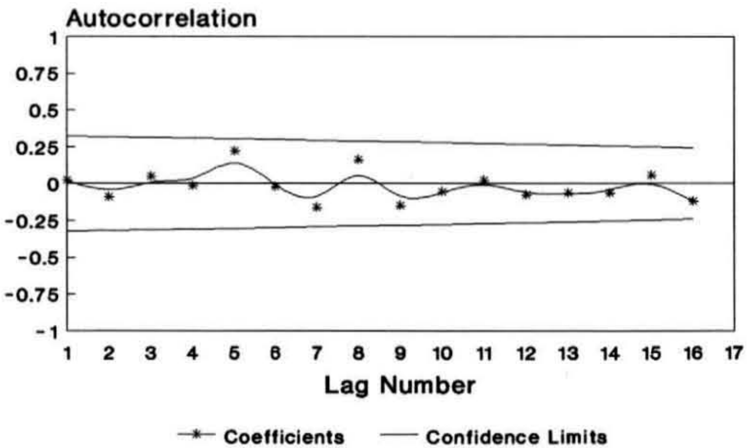


Fig IV.52 Penaeid prawns - Kerala
ARIMA (2,0,0)

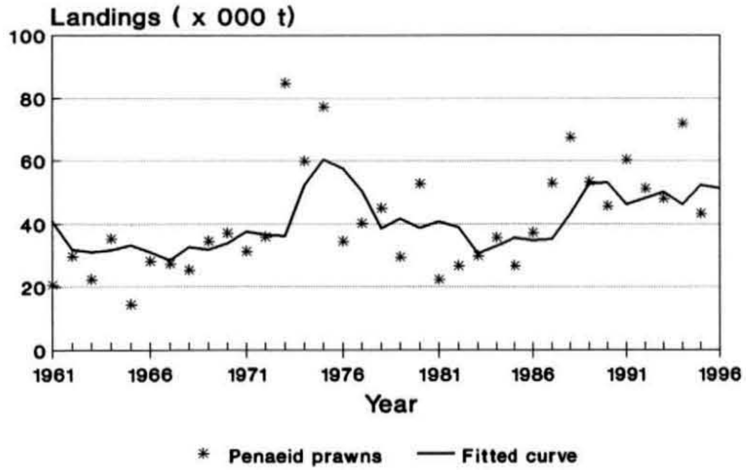


Fig IV.53 Autocorrelation function
Penaeid prawns - Kerala

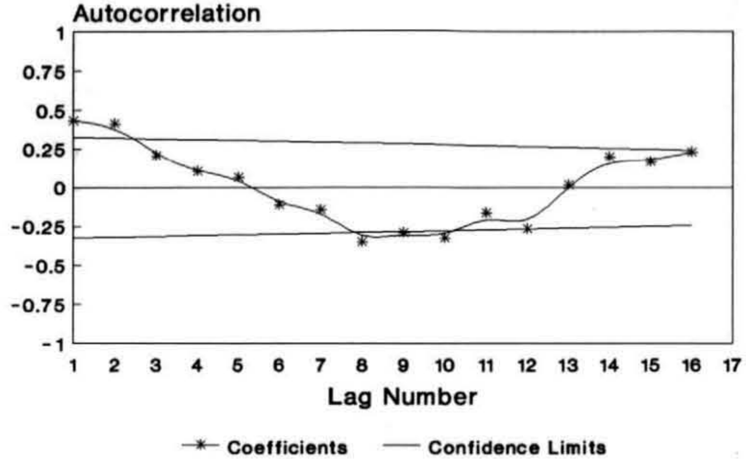


Fig IV.54 Partial Autocorrelation
Penaeid prawns - Kerala

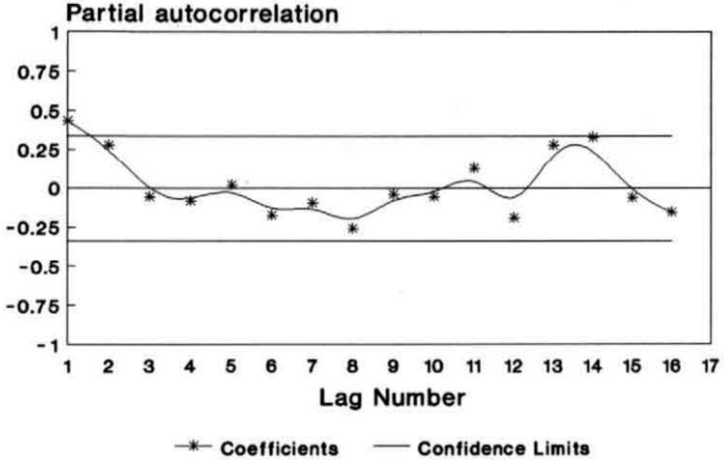


Fig IV.55 Autocorrelation of residuals
Penaeid prawns - Kerala

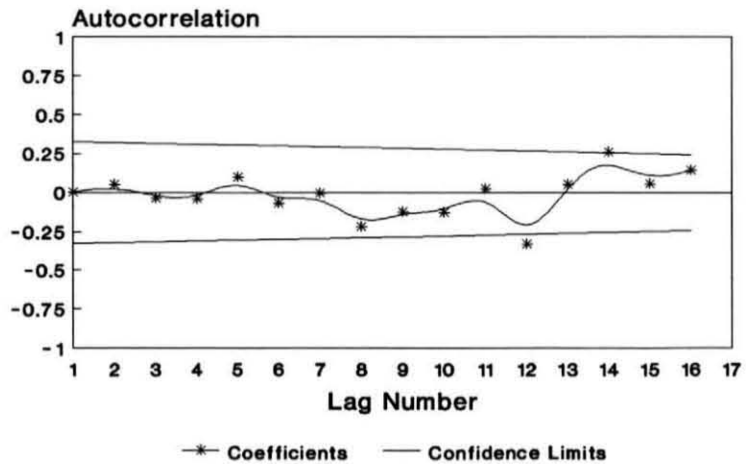


Fig IV.56 Total landings - Tamil Nadu
ARIMA(2,1,0)

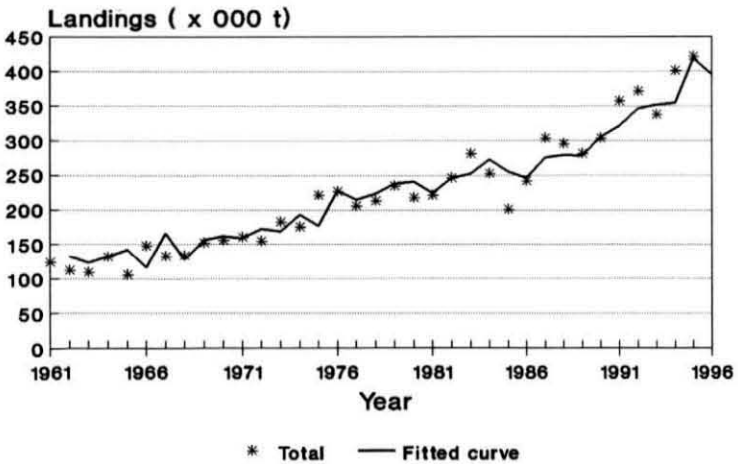


Fig IV.57 Autocorrelation function
Total landings - Tamil Nadu

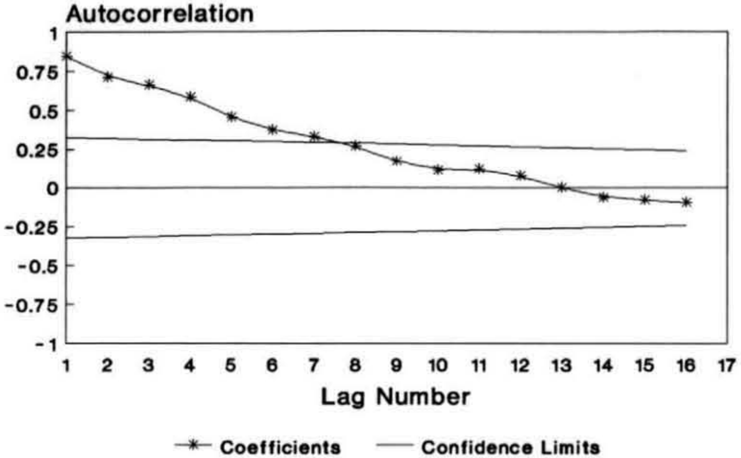


Fig IV.58 Partial Autocorrelation
Total landings - Tamil Nadu

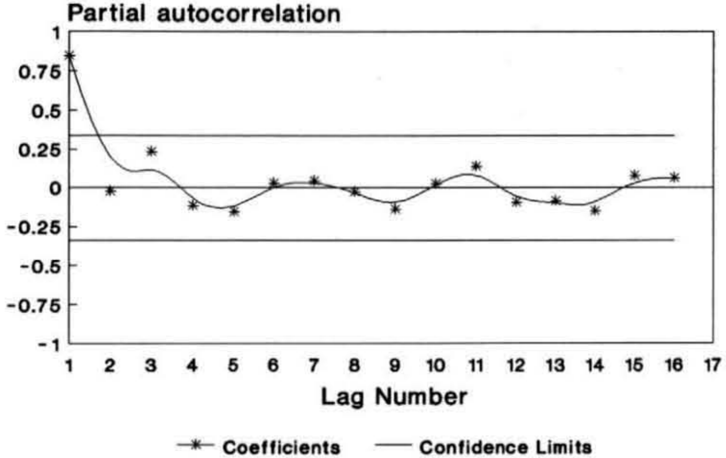


Fig IV.59 Autocorrelation function
Total landings - Tamil Nadu
(FIRST DIFFERENCE)

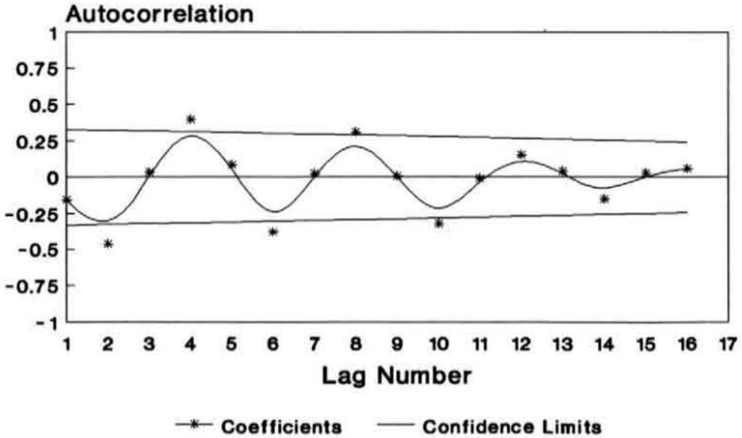


Fig IV.60 Partial Autocorrelation
Total landings - Tamil Nadu
(FIRST DIFFERENCE)

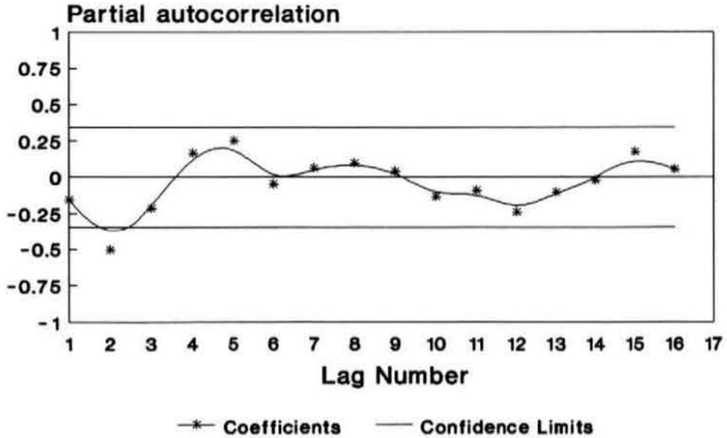


Fig IV.61 Autocorrelation of residuals
Total landings - Tamil Nadu

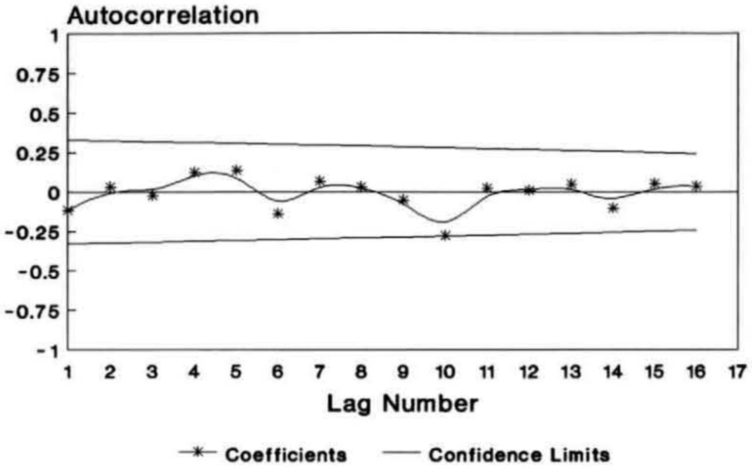


Fig IV.62 Silverbellies - Tamil Nadu
ARIMA (0,1,0)

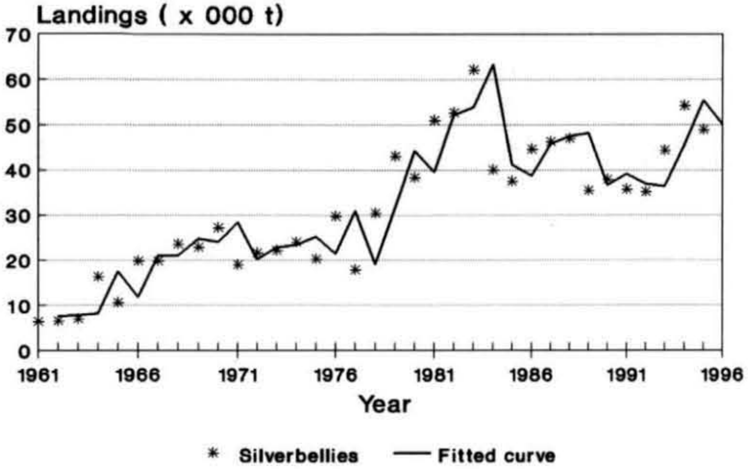


Fig IV.63 Autocorrelation function
Silverbellies - Tamil Nadu

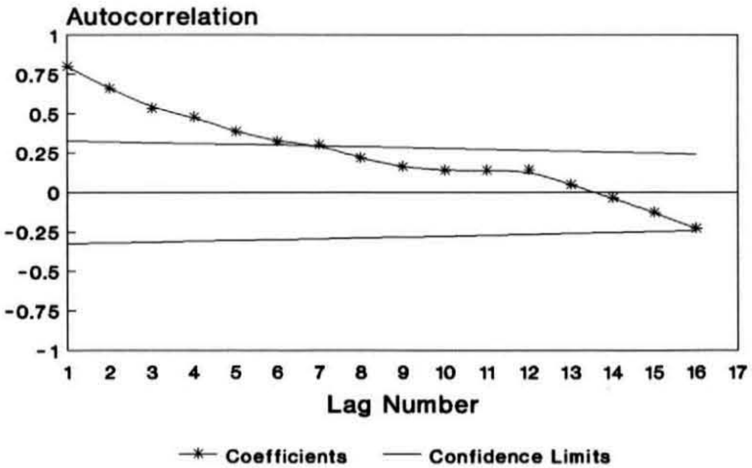


Fig IV.64 Partial Autocorrelation
Silverbellies - Tamil Nadu

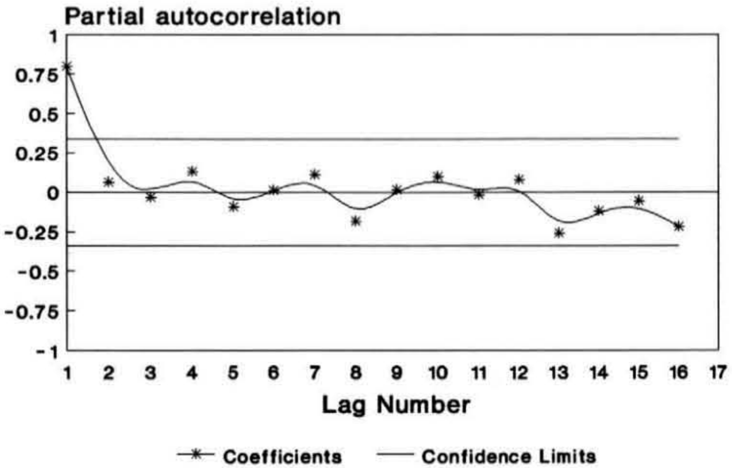


Fig IV.65 Autocorrelation function
Silverbellies - Tamil Nadu
(FIRST DIFFERENCE)

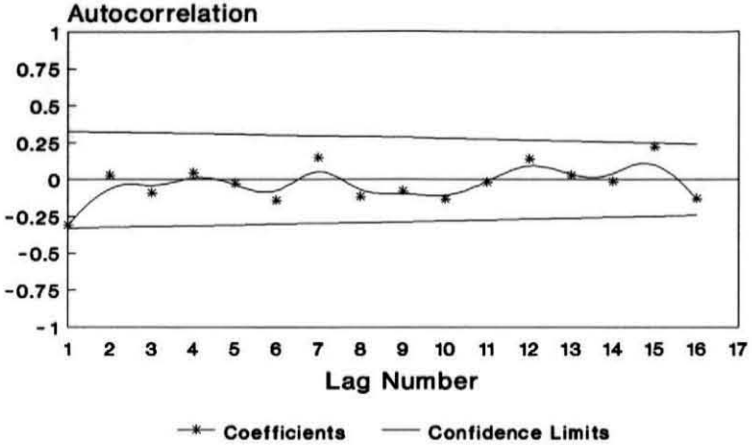


Fig IV.66 Partial Autocorrelation
Silverbellies - Tamil Nadu
(FIRST DIFFERENCE)

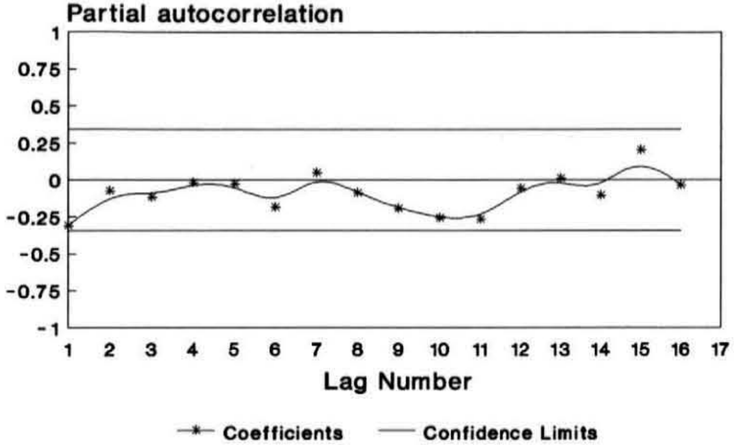


Fig IV.67 Penaeid prawns - Tamil Nadu
ARIMA (2,1,0)

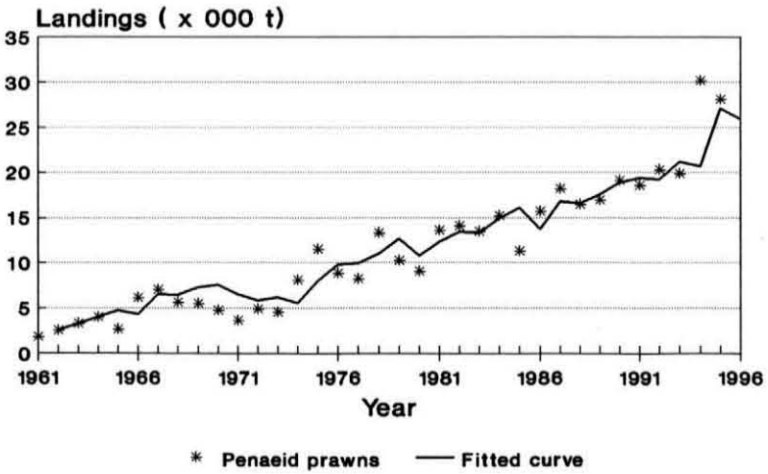


Fig IV.68 Autocorrelation function
Penaeid prawn - Tamil Nadu

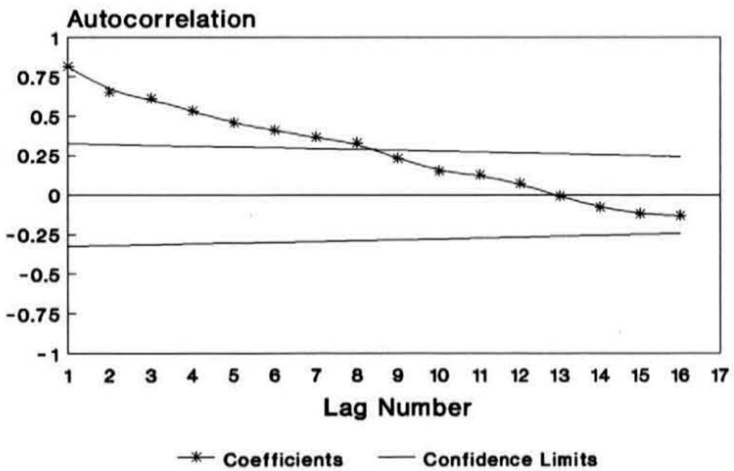


Fig IV.69 Partial Autocorrelation
Penaeid prawns - Tamil Nadu

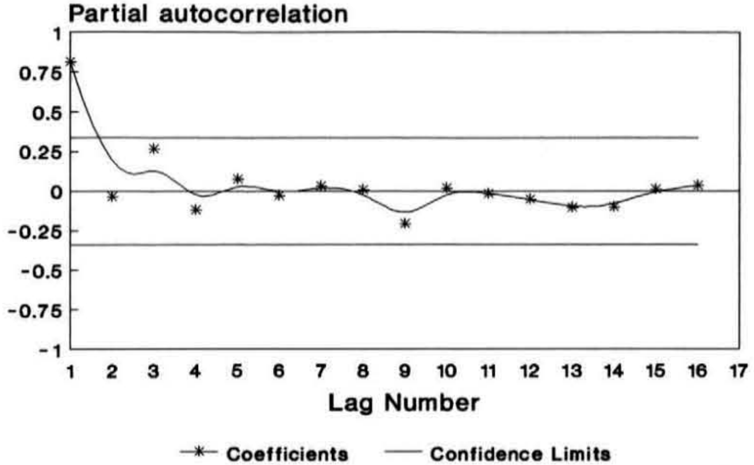


Fig IV.70 Autocorrelation function
Penaeid prawns - Tamil Nadu
(FIRST DIFFERENCE)

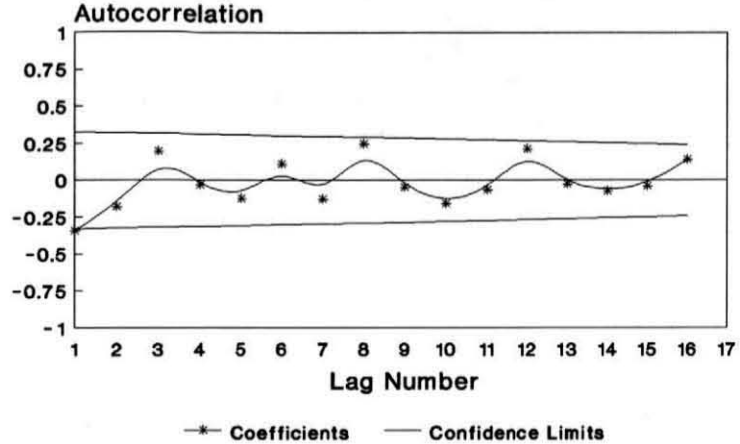


Fig IV.71 Partial Autocorrelation
Penaeid prawn - Tamil Nadu
(FIRST DIFFERENCE)

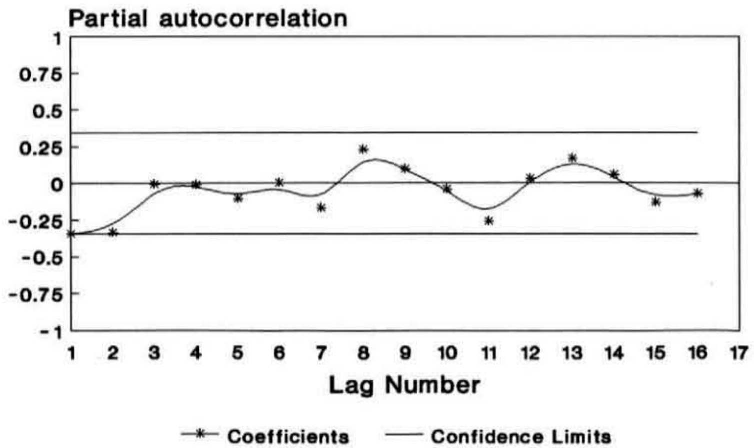


Fig IV.72 Autocorrelation of residuals
Penaeid prawns - Tamil Nadu

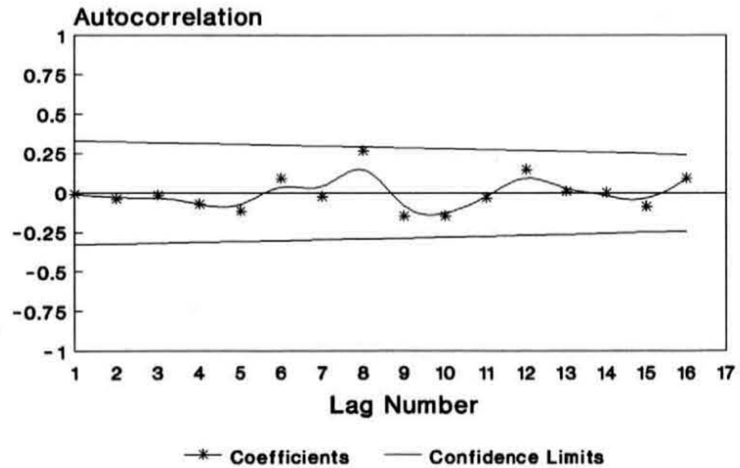


Fig IV.73 Total landings - Maharashtra
ARIMA(0,1,1)

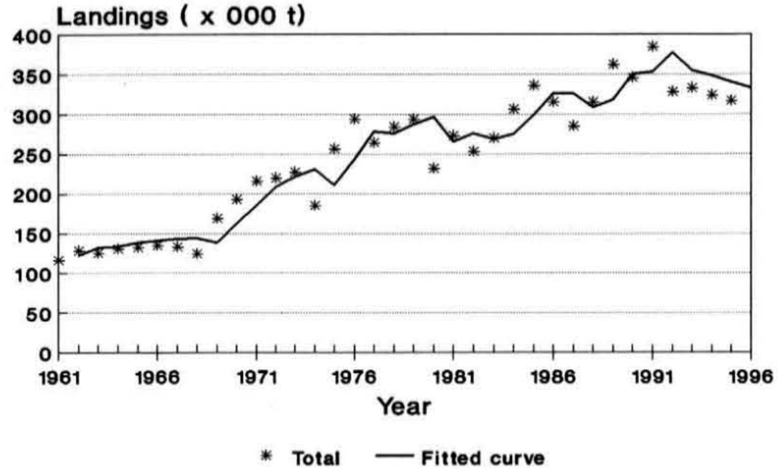


Fig IV.74 Autocorrelation function
Total landings - Maharashtra

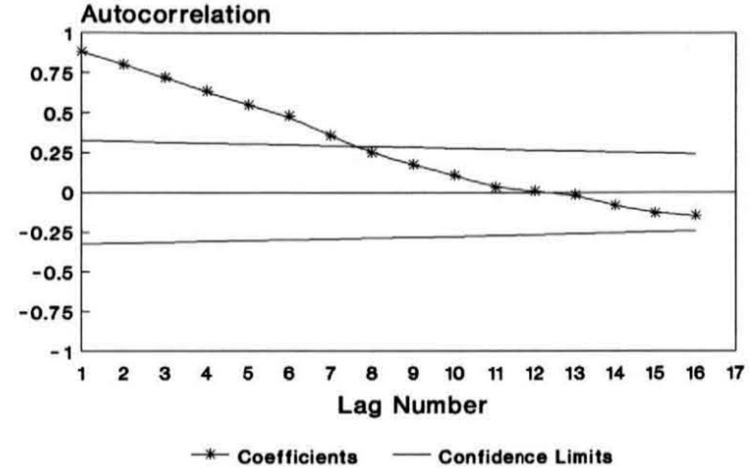


Fig IV.75 Partial Autocorrelation
Total landings - Maharashtra

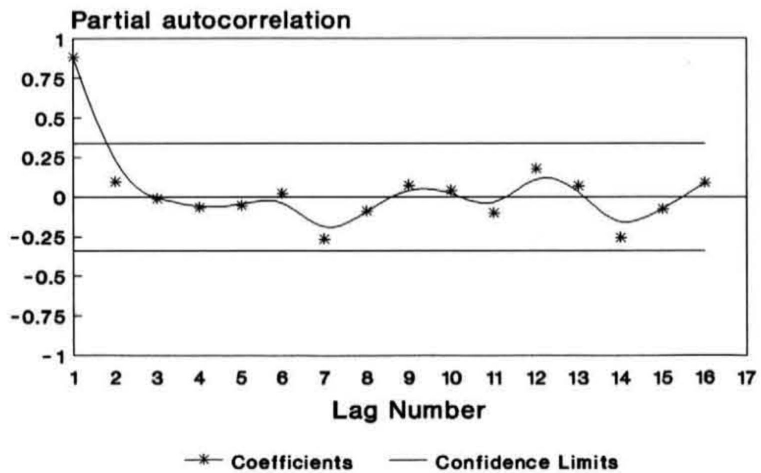


Fig IV.76 Autocorrelation function
Total landings - Maharashtra
(FIRST DIFFERENCE)

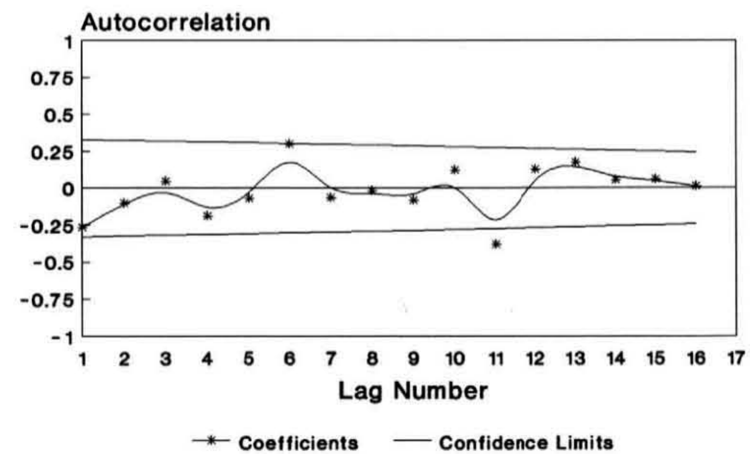


Fig IV.77 Partial Autocorrelation
Total landings - Maharashtra
(FIRST DIFFERENCE)

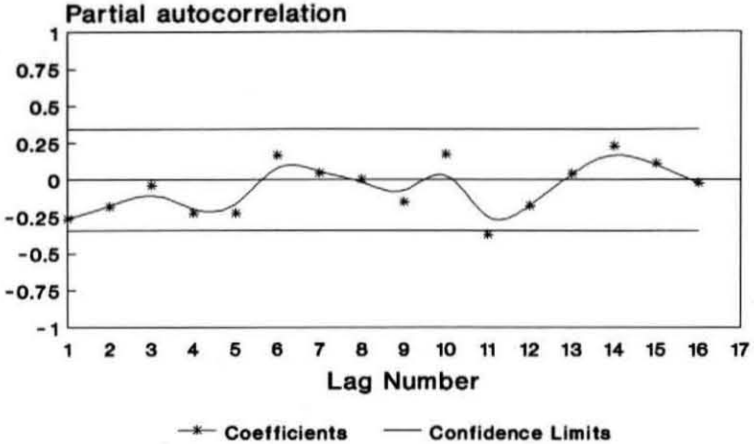


Fig IV.78 Autocorrelation of residuals
Total landings - Maharashtra

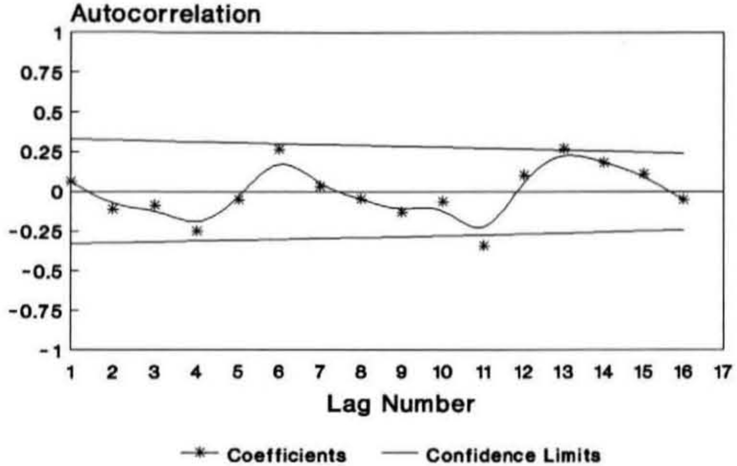


Fig IV.79 Penaeid prawns - Maharashtra
(ARIMA (0,0,1)(2,1,0)6)

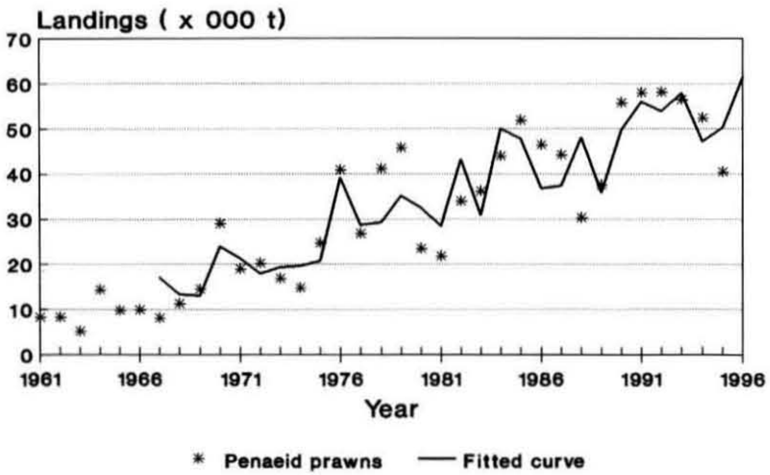


Fig IV.80 Autocorrelation function
Penaeid prawns - Maharashtra

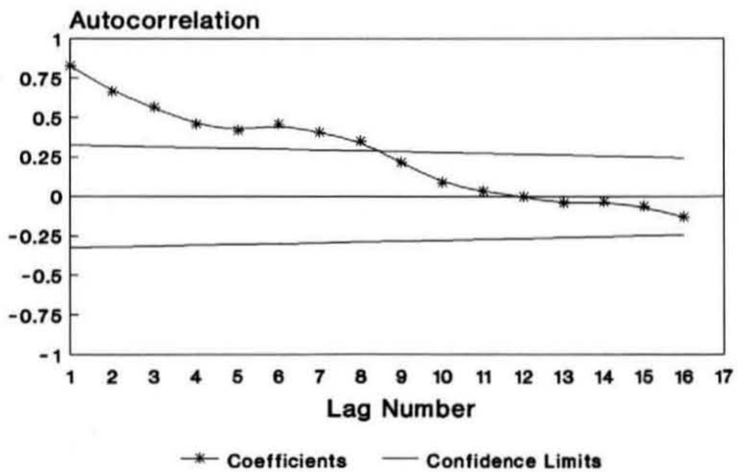


Fig IV.81 Partial Autocorrelation
Penaeid prawns - Maharashtra

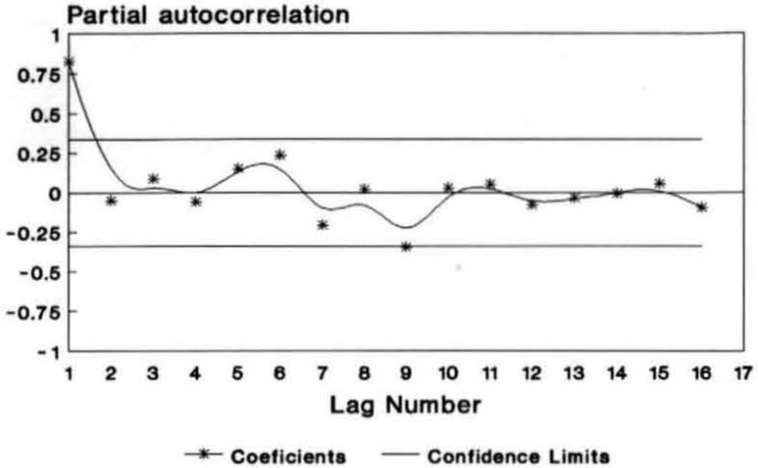


Fig IV.82 Autocorrelation function
Penaeid prawns - Maharashtra
(FIRST DIFFERENCE)

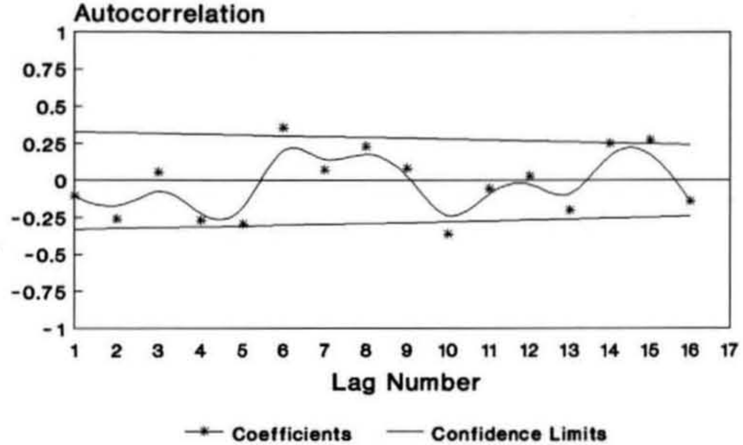


Fig IV.83 Partial Autocorrelation
Penaeid prawns - Maharashtra
(FIRST DIFFERENCE)

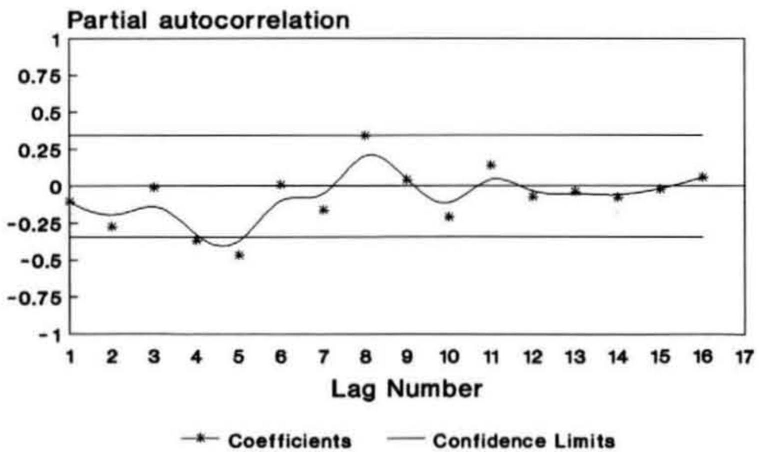


Fig IV.84 Autocorrelation of residuals
Penaeid prawns - Maharashtra

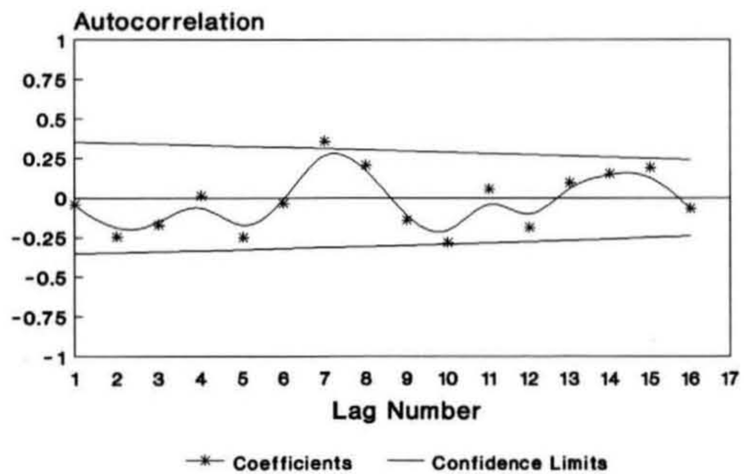


Fig IV.85 Bombayduck - Maharashtra
ARIMA(0,1,0)

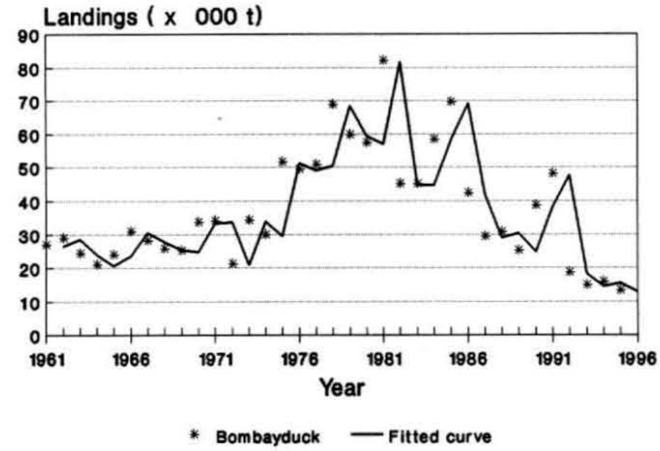


Fig IV.86 Autocorrelation function
Bombayduck - Maharashtra

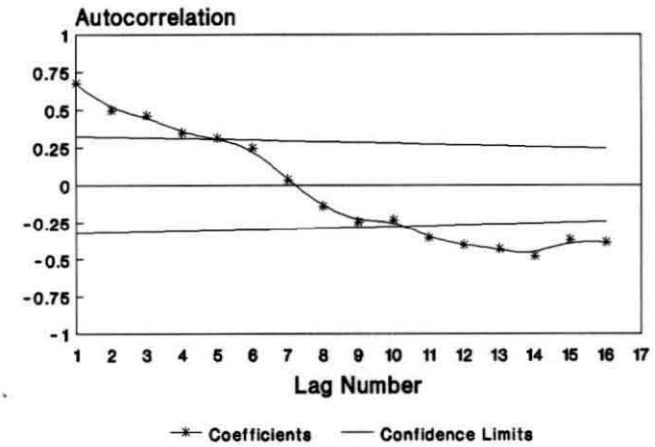


Fig IV.87 Partial Autocorrelation
Bombayduck - Maharashtra

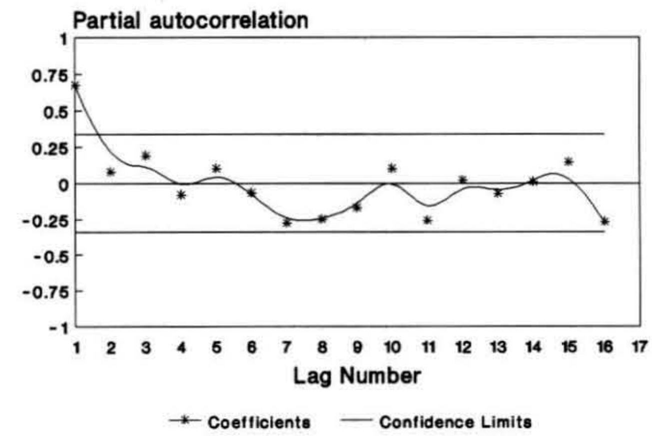


Fig IV.88 Autocorrelation function
Bombayduck - Maharashtra
(FIRST DIFFERENCE)

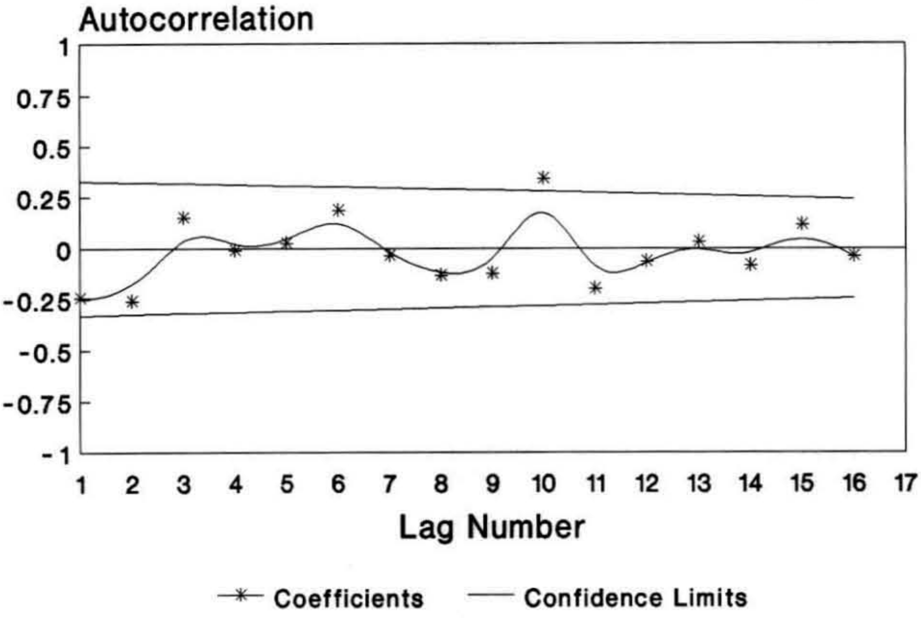


Fig IV.89 Partial Autocorrelation
Bombayduck - Maharashtra
(FIRST DIFFERENCE)

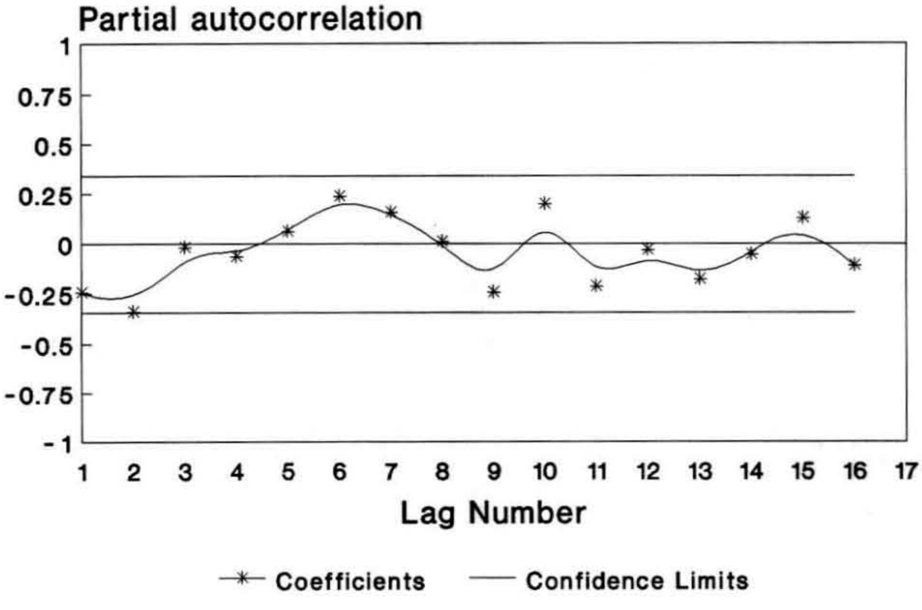


FIG IV.90 OILSARDINE IN RELATION TO SOLAR ACTIVITY (KERALA)

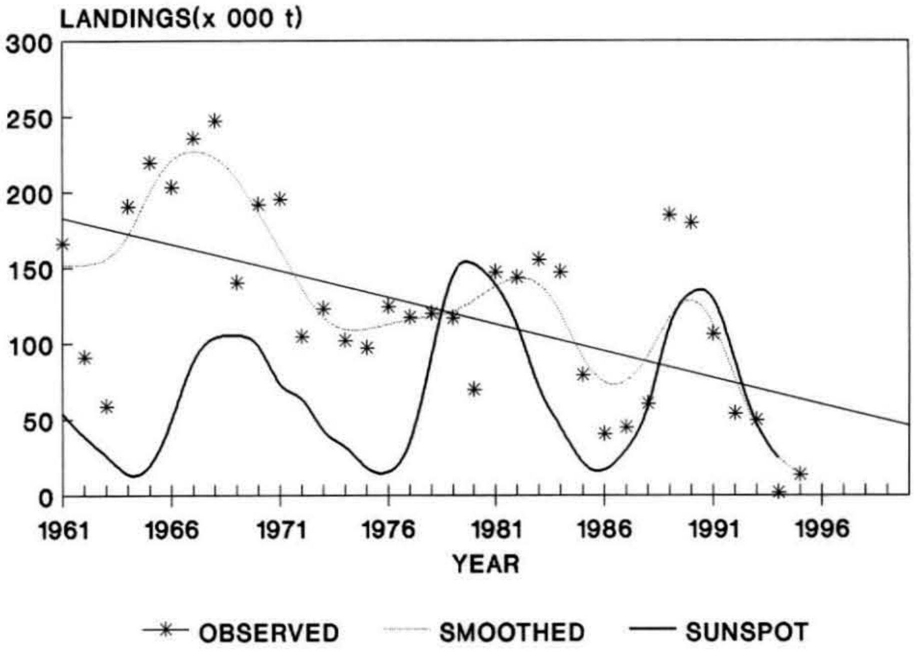


FIG IV.91 OBSERVED AND EXPECTED TREND IN OILSARDINE LANDINGS OF KERALA

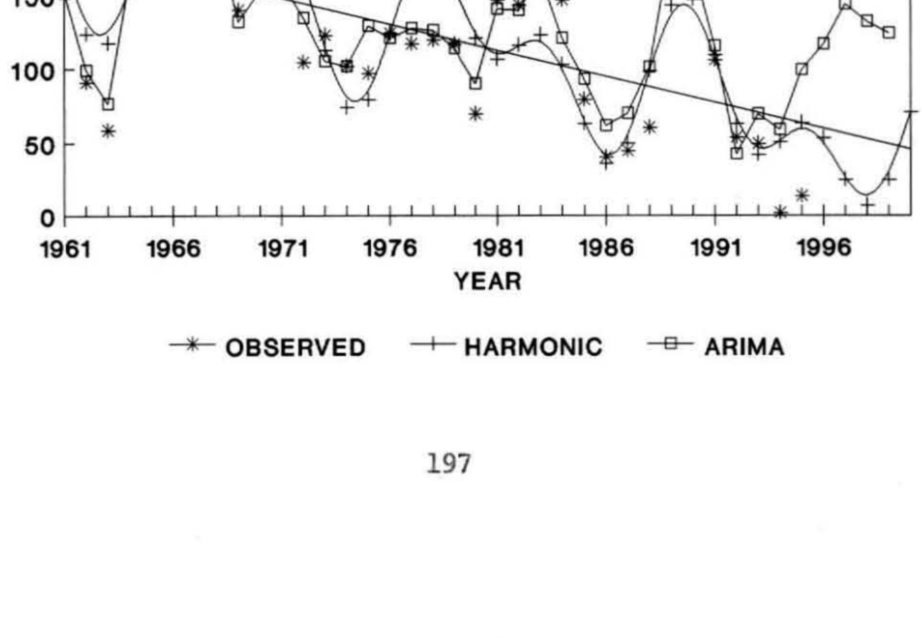


Fig IV.92 Periodogram for residuals of linear trend - oilsardine
KERALA

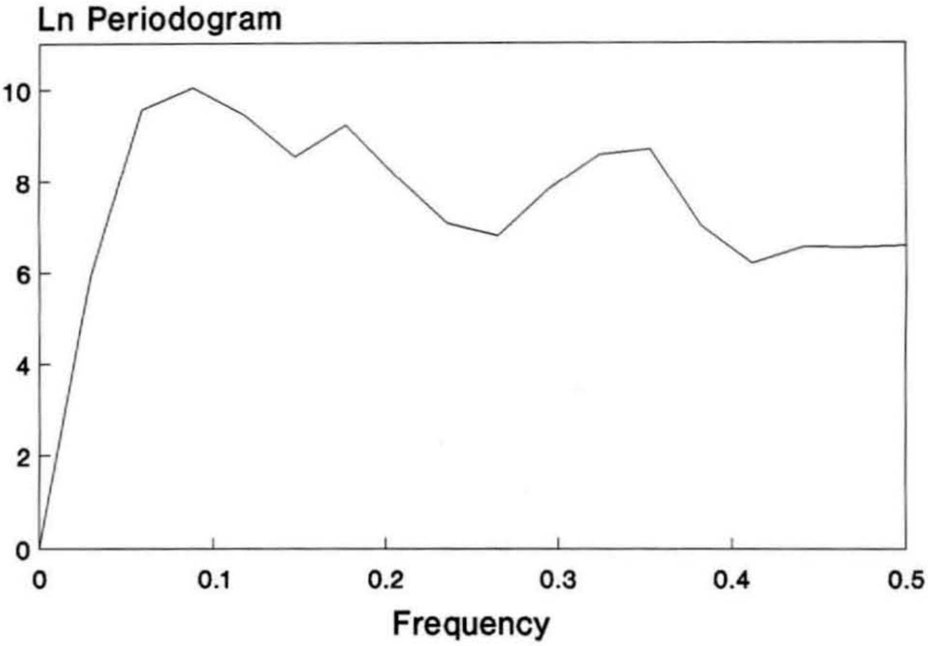


Fig IV.93 Spectral Density for residuals of linear trend - oilsardine
KERALA

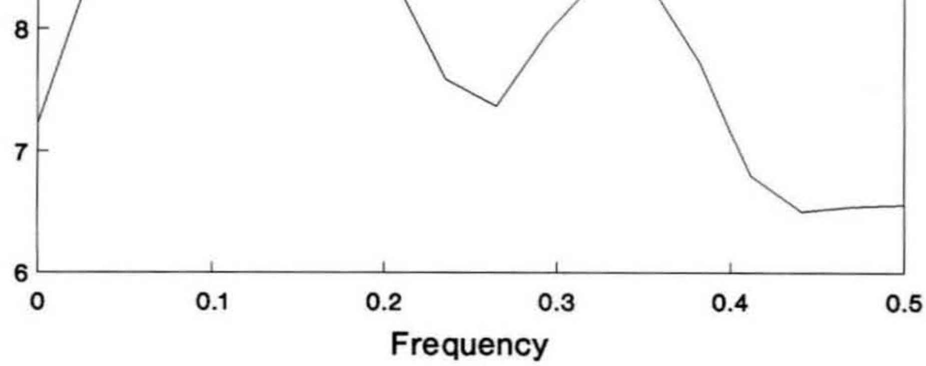


Fig IV.94 Cross Correlation function
sunspot activity with oilsardine catch

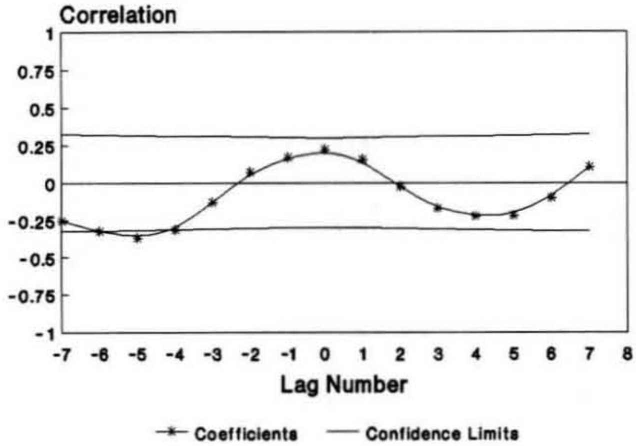


Fig IV.95 Cross Correlation function
sunspot activity with residuals

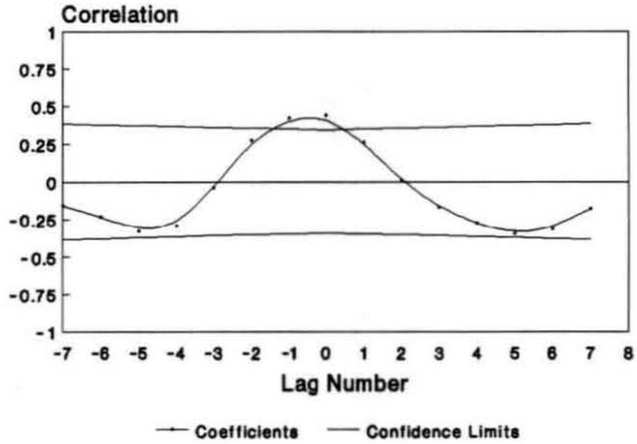
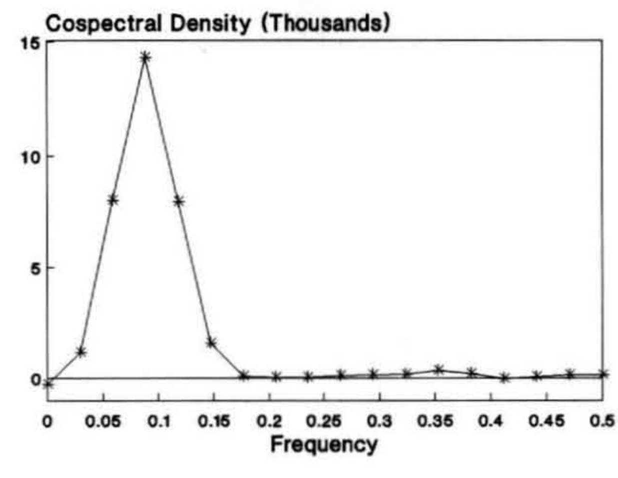


Fig IV.96 Cospectral Density
sunspot activity with residuals



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SUMMARY AND CONCLUSIONS

SUMMARY AND CONCLUSIONS

Simulation techniques are widely used since the popularisation of computers. These techniques help to understand complex systems and also the interplay between the various components of the underlying process. Because of the seemingly unlimited computational power provided by the modern computers, simulation methods are being increasingly used especially in complex dynamic systems such as the marine fisheries. In this study attempts were made to apply simulation techniques in various aspects of exploited marine fish stock assessment.

Eversince the recognition of the economic potential of the marine fisheries sector (especially in India) there is increasing awareness among the fishery managers, resource users and fishery scientists about the need to "manage the fisheries" in order to obtain sustainable yields from the exploited stocks.

Like in any other resource evaluation , marine fish stock assessment requires collection of relevant data (on macro and micro level) , validation of the data, model formulation, estimation of parameters that govern the dynamics of the exploited stocks and finally derive results that would help formulation of appropriate harvesting strategies and also prediction of the yield on a short-term and long-term basis. Some of these aspects have been investigated in this study with the help of simulation techniques.

Validity of the population models and the reliability of the estimated parameters of the model depends largely on the quality of the primary data used for testing the adequacy of the model. In fisheries , catch and effort expended (sometimes catch alone) form important inputs to the production models. The statistics of catch and effort expended on a fishery are usually collected through sample surveys following the principles of theory of sampling. These sampling schemes, in practice , are quite complex , especially so in the Indian context. Evaluation of such sampling schemes is essential from time to time to determine the mode and frequency of data collection. Such an attempt was made in this study where the sampling design to collect marine fish catch statistics in India was investigated on a case study basis. Because of the resource constraints with the Investigator only a single centre ,namely, Cochin Fisheries Harbour, an important landing centre of Kerala was considered. The basic structure of the sampling design is similar to that followed elsewhere in the country. Bootstrap simulation technique was followed to estimate the coefficient of variation in the total catch from the trawlers. The analysis revealed that for a given precision level of 10 to 15% , about 10-12 days observation would be required to estimate the total catch in a given month for the trawl fishery.

Derived forms of Schaefer's production model were investigated with reference to the sensitivity of the model parameters to possible sources of error, namely, the process error (error in the growth equation) and observation error (error in the catch process) . The models were tested for a simulated stock using some initial conditions. The results indicated that the models offer conflicting options in presence of the errors considered. From the management point of view the discrete form of the Schaefer model seemed to perform better than the continuous form, Whereas for obtaining the estimates of model parameters the continuous form seemed a preferable one. However, the simulation analysis revealed that both the models are quite sensitive to errors. The results obtained were in close agreement with similar studies carried out for other production models.

Estimates of mortality rates are vital to analytical yield models. In this study alternative estimator of total instantaneous rate of mortality(Z) was proposed and was compared with some of the classical length based methods such as the Beverton&Holt and the Ssentongo-Larkin estimators. Generalised expressions for average length and variance in length in a time (age interval) were derived. They were

$$L_{bar} = L_\infty [1 - (Z/(Z+K))e^{-Kp} \{ (1 - e^{-(Z+K)})/(1 - e^{-Z})) \}]$$

$$V(L) = L_\infty^2 e^{-2Kp} [(Z/(Z+2K))(y_2/x_1) - (Z/(Z+K))^2.(y_1/x_1)^2]$$

From the mean length L_{bar} the following expression was derived from which the growth parameters could be estimated,

$$\mathbf{L_{bar} = L_\infty [1 - e^{-K(p+0.5)}]}$$

where p is lower limit of the age interval p,p+1 and L_{bar} is the average length in that interval.

From the expressions of mean and variance the proposed estimator was

$$\mathbf{Z_v = 2.K. (v + \theta_2^2)/(\theta_1^2 - \theta_2^2 - v)}$$

In tropical waters where the fish stocks are characterised by shorter life span and the length frequency data is constrained by gear selection, estimation of mortality rates on the assumption of infinite exploitable life span may lead to biased values. This aspect was also investigated in this study, a generalised expression for estimating Z was derived and it is $\mathbf{Z_g = K.\ u / (x - u)}$ based on the mean length

and $\mathbf{Z'_g = K.\ 2(\ v + \theta_2{}^2)/(\ x_1\theta_1{}^2 - \ \theta_2{}^2\ - v)}$ based on the variance.

Catch samples were simulated using the following general expressions for mean and variance in length for constrained finite exploitable life span

$$L_{bar} = L_\infty - (L_\infty - L_c)\ (Z/(Z+K))[\ (1 - e^{-(Z+K)a})/(\ 1 - e^{-Za})]$$

$$V_L\ = (L_\infty - L_c)^2\ Z\ x_1 / (Z + 2K)\ - (L_\infty - L_{bar})^2$$

The performance of the proposed estimator and the two earlier mentioned estimators were compared with respect to relative bias. It was found in most of the cases the proposed estimator and the Beverton&Holt estimator performed better than the Ssentongo&Larkin estimator.

A simple empirical equation for estimating natural mortality rate(M) applicable to tropical fish stocks was derived ,namely,

$$\mathbf{M\ = 0.4615 + 1.4753\ K\ \ with\ R^2 = 84.4\%}$$

The main aim of resource assessment activity is not only to assess the present status of the stocks , suggest appropriate harvesting strategies but also to provide short-term and long-term forecasts which would help the resource users and fishery managers tune their management policies. In this study time series modelling using the Auto Regressive Integrated Moving Average (ARIMA) approach was used to describe some of the commercially important fisheries on All India basis and also for some major maritime states. The results are summarised in the following table.

Region	Fishery	Model	Forecast - 1996
All India	Total	ARIMA(1,1,0)	23.71 lakh tonnes
	Oilsardine	$ARIMA(1,0,0)(1,0,0)_5$	133.81 thousand tonnes
	Bombayduck	ARIMA(0,1,0)	92.69 "
	Mackerel	$ARIMA(1,0,0)(1,1,0)_4$	185.26 "
	Penaeid prawns	ARIMA(0,1,1)	202.84 "
Kerala	Total	ARIMA(0,1,0)	539.38 "
	Oilsardine	$ARIMA(1,0,0)(1,1,0)_4$	61.84 "
	Mackerel	$ARIMA(1,0,0)(1,1,0)_3$	58.91 "
	Penaeid prawns	ARIMA(2,0,0)	51.42 "
Tamil Nadu	Total	ARIMA(2,1,0)	395.66 "
	Silverbellies	ARIMA(0,1,0)	50.18 "
	Penaeid prawns	ARIMA(2,1,0)	25.92 "
Maharashtra	Total	ARIMA(0,1,1)	332.85 "
	Penaeid prawns	$ARIMA(0,0,1)(2,1,0)_6$	61.42 "
	Bombayduck	ARIMA(0,1,0)	13.00 "

A significant finding of this investigation was establishment relationship of oilsardine landings of Kerala with the solar activity (mean annual sunspot numbers). The analysis of the data revealed there is concordance of the 11- year sunspot activity with the periodic variation in the oilsardine landings of Kerala.

Thus this study clearly brought out the usefulness of the simulation techniques in marine fish stock assessment and derived some important results. There is tremendous scope to enhance the present study. An important aspect which needs further research is how best the fishery dependent and independent factors could be incorporated in a production model for a clearer understanding of the dynamics of the exploited stocks. The forecasting models could also be developed by including the auxiliary information of the fisheries for arriving at more precise forecasts. For this Vector Auto Regressive Moving Average approach could be attempted. The relationship of solar activity with the oilsardine fishery needs in-depth research, which includes identification of inter-linking mechanisms. The bootstrap evaluation of the sample survey obviously needs to be extended to other fisheries and could be tried on a larger area which would help the fishery administrators to arrive at reliable fishery statistics.